EMPIRICAL ANALYSIS OF SHORT-TERM VARIABILITY FROM UTILITY-SCALE SOLAR FARMS IN NORTH CAROLINA

A Thesis
by
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Abstract

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The core purpose of this study was to investigate the issue of resource intermittency and variability of solar power at the utility scale. Variability remains a primary driver of increased cost associated with integrating solar into the electric grid, along with the supplementary resources required to maintain its reliability.

Using data collected from three individual utility-scale solar farms in North Carolina, this research sought to characterize the variability using irradiance and power data collected at a 15 minute temporal resolution. This was accomplished primarily by using the "variability index" to quantify, categorize and compare variability across the three locations. This allowed for the identification of days of highest and lowest variability at each site, along with comparison across all three sites at the same time step.

Additionally, this study explored the effect of geographic dispersion in regards to the "smoothing" of solar variability. This was accomplished by creating an aggregate generation profile for all three sites, and comparing the behavior of this simulated generation to the actual, measured generation at each individual site. Comparison amongst days of highest measured

variability with the aggregate profile seemed to reveal a significant reduction in the magnitude of ramp events. In order to affirm these initial findings, a secondary analysis was performed of these ramp events using AC power (kW).

Ultimately the data revealed a significant reduction in these ramp up/down events, with the largest ramp rates reducing by nearly half in most cases. These reductions can be seen most clearly in the comparative frequency distributions of ramp events. Within these distributions there is a clear shifting of ramp events inwards towards the lower magnitude bins.

Overall, these findings reveal that geographic dispersion of utility-scale solar farms can reduce the variability and volatility of solar power production. With proper planning and placement of photovoltaic plants, effective mitigation of resource intermittency is possible.

Acknowledgments

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CHAPTER 1: INTRODUCTION

Introduction

Reliance upon electricity in this modern era of technological innovation and robust growth is a central concern to society at large. Its function and reliability are paramount to driving progress throughout the nation and world. Due to the critical role that electricity plays in our development and national security, and to concerns about how this electricity is generated, increased attention has been paid to reducing dependency on carbon-based fuel sources that are procured largely under delicate and costly geopolitical relationships. A promising result of this interest has been investment in renewable sources of electrical power such as wind and solar, which reduce externalities and environmental expense while also reducing vulnerability to global political disturbances.

As the United States attempts to incorporate renewable sources of energy into the electrical power generation sector, attention must be paid to their fundamental differences from conventional power plants and fuels. Traditional power plants that use fossil fuels, and rely on combustion and steam turbines, can be easily dispatched to provide power output to the grid. Conversely, most renewable sources that are being introduced to the power production mix are variable, meaning their power output fluctuates according to natural cycles or patterns, some of which are not easily predictable. Power generated through a solar resource is subject to variation in not just the rise and fall of the sun throughout the day and year, but more localized variations caused primarily by cloud cover. "The highly predictable diurnal and annual irradiance pattern aside, clouds have the strongest impact on solar energy production. Transient clouds cause strong spatio-temporal variability and fluctuating solar power feed-into the grid" (Chow, Belongie, & Kleissl, 2015, p. 645). This fluctuation of renewably-generated power into the grid system, which is largely unpredictable, is a cause of concern for those managing the infrastructure and transmission of power within particular service areas or regions. Concern arises out of the cost of mitigation and control of the fluctuation, as well as how to best accommodate the variable nature of wind and solar into a grid, that is in many ways unprepared for widespread incorporation of variable power sources.

Governments at the federal and state level are imposing requirements for adoption of renewable energy sources through Renewable Portfolio Standards (RPS) and other programs, therefore increasing the incorporation of renewables into various states' energy portfolios. Tarroja, Mueller, and Samuelsen (2013) recognize the influence that this increased incorporation will have by acknowledging "as solar power becomes an increasingly large fraction of the electric power generation portfolio, solar intermittency characteristics will become increasingly significant" (p. 1003). It follows that it is in the best interests of governments, utilities, and developers to better understand the impact intermittency can have on the function of the grid. Intermittency, defined simply, is a term used to describe the variability associated with using the sun (or wind) as a source of energy. Because these fluctuations are often short-term and can be observed at timescales down to one second, predicting the variance is not a practical approach to mitigating its adverse effects. Instead of focusing efforts on anticipation of cloud cover and weather events, a better solution lies in properly buffering against large-magnitude fluctuations with dispatchable generators, storage, regulation capacity, and/or ancillary services to accommodate the adoption of photovoltaics (PV). The priority for stakeholders and governments thus becomes "characterizing and finding methods to alter the character and magnitude of these fluctuations," and determining how to best advise the development of solar resources (Tarroja et al., 2013, p. 1003).

Considering the ongoing transition to renewable energies and the technical difficulties involved in such a transition, research is needed on how to best incorporate these technologies while avoiding a reduction in the grid's reliability. PV in particular holds promise both at the residential level and at the utility scale. This research focused on solutions for better understanding the development of large scale PV in North Carolina to better inform decisions regarding its future incorporation into the electric grid and improve system operator's ability to handle such a transition.

Statement of the Problem

Solar power has become a fast-growing and ever-present technology in North Carolina, with a majority of PV development in the form of large, utility scale (>1MW) solar farms. Although solar power's baseline diurnal variability is fairly predictable, there are still significant variations that occur through changes in daily weather, such as cloud cover. Quantifying this variability is essential to understanding how higher levels of PV penetration will affect the grid and its reliability. Upon successful quantification of variability, fluctuating degrees of variability can be identified. These assignments can help researchers or system operators make further inquiries into mitigation tactics for reducing the negative impacts of intermittency. One tactic that has been researched within the solar community, is reduced volatility through aggregation of generation profiles at geographically dispersed site locations (Wiemken, Beyer, Heydenreich & Keifer, 2001; Lave & Kleissl, 2010, 2011, Golnas, & Voss, 2010). That is to say that the intermittency observed by a collection of systems throughout a diverse geographic area will be less volatile than that of a single system. Such analyses can be performed after identification of highly variable days within an observed geographic area.

Efforts have been made to quantify the fluctuations caused by intermittency throughout the past few decades. A study by Wiemken, Beyer, Heydenreich, and Kiefer (2001) used data collected from 100 PV systems throughout Germany in an attempt to analyze the effects of combined power generation as compared to individual systems. Golnas and Voss (2010) observed variability of PV system fleets in several service territories in California and New Jersey to assess the variability and implications of various levels of dispersion. These studies were able to use production data from systems in Germany, California, and New Jersey to empirically observe the smoothing effect that many, spatially-distributed PV systems can have on the aggregate generation profile. Although these and other studies have looked at the effect of spatial distribution of solar generators on aggregate generation profiles, studies using actual production data to make conclusions about variability that are geographically specific to North Carolina are non-existent to date. Because North Carolina has become a breeding ground for utility-scale PV development, the opportunity to analyze measured production data from currently-operating utility scale PV systems in NC can offer much-needed insight into the extent to which the spatial distribution of PV projects mitigates weather-induced fluctuations in output, and can offer guidance to future growth.

Purpose of the Study

The purpose of this study was to analyze the variability of Global Horizontal Irradiance (GHI in W/m^2) as a proxy for AC power production (kW), measured at three utility-scale solar farms in North Carolina using data from a leading operations and maintenance company portfolio. Solar irradiance received at the Earth's surface is highly variable in nature, which leads to the variability of power produced by PV panels (Huang, Troccoli & Coppin, 2014, p. 195). The primary observations, therefore, focused on irradiance across the three sites, with AC power production used as confirmation of the assumption that irradiance can be used as a proxy. A variability metric (discussed later) was employed to assign a numerical value to the degree of daily irradiance. Knowledge acquired from these assignments of value can assist in further research dealing with integration of variable generation into the grid and necessary ancillary services required to maintain its robustness. Finally, this study sought to understand if this sample's relatively low spatial diversity (>125 miles) reduced the geographic-smoothing effect. Research has suggested that greater "spatial diversity reduces the magnitude of the fluctuations in power output as a fraction of the total system capacity" (Tarroja et al., 2013, p. 1004). In other words, a spatially diverse distribution of solar farms throughout a defined geographical area would alleviate short time-scale fluctuations in productivity that aggravate the already disruptive flow of solar energy. This research was conducted to add to our understanding of a spatially diverse solar farm portfolio to the aggregated total capacity as well as to provide methods for identification of deviations from normal diurnal solar cycles caused by atmospheric interruptions such as cloud cover.

Research Questions

RQ1- What is the variability at a 15 minute temporal resolution of Global Horizontal Irradiance (W/m^2) at all three sites included in this analysis?

RQ2- To what extent does aggregating AC power (kW) production from three distributed PV farms affect variability, when compared to power production at the individual farms?

Assumptions

A PV plant's power output depends on the solar irradiance which can fluctuate as clouds pass overhead (Gagné, Turcotte, Goswarmy, & Poissant, 2016, p. 46). Solar irradiance is therefore directly related to the ultimate output of a PV plant. There is some dependence, however, on temporal resolution of the irradiance and power data when considering the translation of irradiance data to power output. Irradiance meters (pyranometers) can show more severe ramp rates in time scales up to 10 minutes, as compared to power output of a plant whose capacity is in the megawatt scale. However, fluctuations in irradiance for time scales longer than 10 min, will be more similar to changes in power output for a plant whose capacity is in the megawatt scale (Mills, Ahlstrom, Ellis, & Hoff, 2011, p. 37; Haaren, Morjaria, &

Fthenakis, 2012, p. 555). In other words, point measurements taken with a pyranometer in short time scales (<10 min), will exhibit more bimodal (on/off) behavior than the subsequent output due to smoothing that takes place over the full area of the PV plant. However, irradiance data taken at longer time scales (>10 min), will be more similar to said PV plant's output. It is therefore an assumption throughout this study that irradiance data can be used as a proxy for resulting power production.

Limitations of the Study

The primary limitation to this study is the temporal resolution of the irradiance and power measurements analyzed. Because variability caused by rapid cloud movement and weather related events can occur at a very short timescale, 15-minute resolution data may overlook changes in irradiance and power production that occur within that interval . In a study conducted by Lave, Reno, and Broderick (2015), solar variability was simulated by observing transformer tap changes in various timescales. On-load tap changers are a form of regulation control that seek to correct voltage fluctuations caused by solar variability in PV (Lave, Reno, & Broderick, 2015, p. 327). Transformer tap changers on distribution feeders often have time constants as short as 30 seconds, therefore justifying the use of high-frequency GHI data in their analysis. This study used simulations to illustrate the effect different irradiance profiles have on voltage regulator tap change operations. These researchers encountered errors of up to -70% when using low-frequency (15-minute) data, leading to significant underestimation of tap change operations (Lave et al., 2015, p. 327). This indicates a potential limiting factor because the intervals at which the data are measured and recorded may also underestimate variability that would have implications for potential mitigation or a deeper understanding of the variability at a particular location. In summary, Lave et al.'s research concluded that significant fluctuation in irradiance can occur at very short timescales, and thus temporal resolution that exceeds subminute ranges can overlook fluctuations that may be important for grid operation and mitigation efforts. Another study found that even using a recording period longer than 400 milliseconds would possibly lead to underestimating variability (Gagné et al., 2016, p. 46).

In order to analyze the variability of the irradiance samples, a clear sky index was needed for direct comparison to the measured data. The Bird Clear Sky Model (Bird & Hulstrom, 1981) adapted into an Excel spreadsheet provides measurements at a 1-hour timescale for the entire year. In order for these data to be synchronous with the measured data from the solar farms, a simple linear interpolation had to be conducted to reveal the three intervals (15 minute) within the hour that were previously missing. Because the model allows for manual entering of time intervals, a comparison can be made between the model and the interpolation results, which in all the sampling conducted revealed a less than 2 percent error in all cases. Because these simulated data contain some error where interpolation was used, it is presented as a potential limitation.

The proprietary nature of PV farm output data limited the sample size to three solar farms, restricting much of the geographic diversity that would have benefitted my ultimate research goals.

Utility territory was not a consideration in this study, but rather a geographic boundary that contains a hypothetical "grid." That is to say, details involving the interconnection, such as location of transformers, loads and whether the PV generation feeds to the distribution or transmission lines, were not considered, but instead all variability was considered to have an equal effect from each farm included in the study.

Other limitations included the geographic specificity that the study sought to operate within, meaning findings from this study may not necessarily apply to another geographic region. Behavior of cloud and greater weather patterns are diverse and vary from region to region, making subsequent variations in observed power output just as regionally specific. A 2009 Unites States Department of Energy (USDOE) report titled *Understanding Variability and Uncertainty of Photovoltaics for Integration with Electric Power System* noted that "data sets from multiple regions need to be analyzed and compared to determine the extent to which local features affect the smoothing benefits of geographic diversity" (United States Department of Energy [USDOE], 2009, p. 7). This suggests that topography, climate, and many other factors specific to a location will affect the degree to which the dispersion-smoothing effect can function. This is not necessarily a strict limitation as much as it imposed a specificity that may limit broader applicability of my findings.

Significance of the Study

This study is significant for the future development of utility-scale photovoltaic farms within the state of North Carolina and elsewhere in the world. Developers and regulators in the solar industry will have an interest in the results of this study because it could inform future knowledge of the behavior of irradiance and resulting power production in North Carolina, and open the door to potential methods of mitigation. Identification of any deviation from the expected, normal diurnal cycle is beneficial to the understanding of the behavior of solar energy regardless of the cause. This study provides methods that are useful in identification of these deviations, and therefore opens a path to further understanding of intermittency and its eventual mitigation. Several studies show that aggregation of solar power output across a geographically diverse area can lead to a reduction in variability (Wiemken et al., 2001; Lave & Kleissl, 2010, 2011; Golnas & Voss, 2010). These studies have not, however, explored the variability of irradiance and power in North Carolina specifically. Although the relatively small sample size can be presented as a limitation, it may also present an opportunity to provide empirical evidence that despite having a relatively close (less diverse) geographic proximity ($<$125 miles), the variability may still be reduced when aggregated.

CHAPTER 2: REVIEW OF LITERATURE

In order to properly address the research questions proposed, it is important to set the stage for how the study relates to the discipline in the wider picture. This will be done initially by exploring the current state of solar in the United States and North Carolina, as well as projections for the industry going forward. Following the industry briefing, exploration into the characteristics of intermittent power sources will set the stage for the importance of this research. In reference to the second research question, some background is provided for the dispersion-smoothing effect. Proper explanation of the benefits of this effect is important for justifying the need for this research. Lastly, this information is tied back into the larger picture of grid-function, which is not explored in depth in the research but is ultimately the reason for mitigation tactics such as the dispersion-smoothing effect.

Solar PV Production Domestically and in North Carolina

Development of renewable sources of energy continues to be at the forefront of the transition towards reduced dependency on fossil fuels and methods for combatting the threats posed by climate change. Although most of this growth during the early stages has relied heavily on government incentives such as tax breaks and subsidies, drastic reductions in prices of renewable energy technology and increased interest from the private sector have contributed largely to the ultimate goal of making these sources as cheap as their conventional alternatives, a circumstance known as grid parity.

Solar, in particular, has seen unprecedented growth in the past decade, spurred in large part by falling prices of PV modules and associated technologies. A sharp increase in mass production in places like China can be attributed to these price drops. According to the Solar

Energy Industries Association (SEIA), 40% of all new 2015 electricity-generating capacity in the first half of the year was supplied by the solar industry (Solar Energy Industries Association [SEIA], 2015). Of that growth, residential and utility-scale markets have seen the lion's share. While the cost of residential installation has seen substantial decline, utility-scale costs have seen the most significant drops, with some more recent contracts at prices below $0.05/kwh (SEIA, 2015). This insight into the growth of utility-scale solar is important for North Carolina, where nearly all recent development has been in the form of utility-scale farms. Of the 1,160 MW of solar electric capacity installed in 2015, 1,114 MW was in the form of utility-scale farms (SEIA, 2015).

Various markets exist within the solar industry, from manufacturing to contracting, installation, project development, distribution, financing, engineering, and legal support. There are currently more than 211 solar companies operating in North Carolina alone (SEIA, 2017). Ranked second in the county for installed solar capacity, North Carolina's 3,015.8 MW has jumped significantly from the 923.0 MW in 2016 (SEIA, 2017). Many notable projects can be found in North Carolina, including one of the largest corporate PV systems in the state, developed by Apple Corporation and possessing the capacity to generate 20 MW of electricity (SEIA, 2017). Because the vast majority of this installed capacity is in the form of utility-scale projects, North Carolina offers a unique insight into the dynamics of incorporating large-scale PV into the grid.

Nature of Intermittency and Power Variability

Intermittency in the context of PV generation can most easily be described as interruptions in power generation due to anticipated changes in the sun's location, or to more localized, unanticipated interruptions due to weather and cloud cover. Predictable changes can be attributed to knowledge of solar geometry and tracking of the sun's location throughout the year at a given coordinate. Less predictable and inconsistent are those changes caused by motion and evolution of cloud fields (Kleissl, Perez, & Hoff, 2013). These inconsistencies are sometimes cited as the most significant barrier to PV's large-scale integration into the grid (Kilma & Apt, 2015, p. 1).

Diurnal versus Short Time Scale Variations

When considering what factors will contribute to the fluctuation of production from a PV module, it is essential to understand solar energy as a resource. Unlike conventional fuel sources for generation such as coal, gas, or nuclear, the sun is a variable resource, meaning its availability is often inconsistent. One important distinction that must be made is differentiating diurnal and annual irradiance patterns from the short-term, second-to-second changes caused most often by cloud cover. Diurnal patterns, within the context of PV production, represent the normal generation profile expected throughout a given day as the sun rises and falls. Irradiance and PV production have a direct relationship, meaning when irradiance is at its maximum, so too is production from the PV modules. There are, however, fluctuations within that same time frame that are unpredictable and that change rapidly. In their study, Chow et al. (2015) noted, "highly predictable diurnal and annual irradiance pattern aside, clouds have the strongest impact on solar energy production" (Chow et al., 2015, p. 645). It is these unpredictable, highly disruptive changes that are of primary concern to this study.

Methods for Quantifying Variations

Properly identifying and subsequently quantifying the aforementioned disruptions in production caused by passing clouds is critical for PV research. These observations offer insight that is important for grid operators and for the energy sector in general. Small clouds passing over a PV installation can essentially cause production to go from full to nearly none and back to full again within seconds. In order to capture the significance of these changes in production, observation of production values from a PV system itself can be made, or alternatively, proxies for production such as Global Horizontal Irradiance (GHI) can be measured. Reno, Hansen, and Stein (2012) noted that GHI can be viewed as all of the solar radiation on a horizontal surface, including the diffuse radiation incident and the direct normal irradiance. The power of sunlight (as well as GHI) is measured in W/m^2, information that can then be translated into maximum output for a PV system (Reno et al., 2012). To capture the variability due to weather and clouds, comparison can be drawn between GHI and GHI clear-sky index (Figure 1), which is essentially an uninterrupted, cloudless day of sun at a given location (Kleissl et al., 2013). This measurement is often taken with a pyranometer, and is included in archived Typical Meteorological Year (TMY) data (Kleissl, 2013).

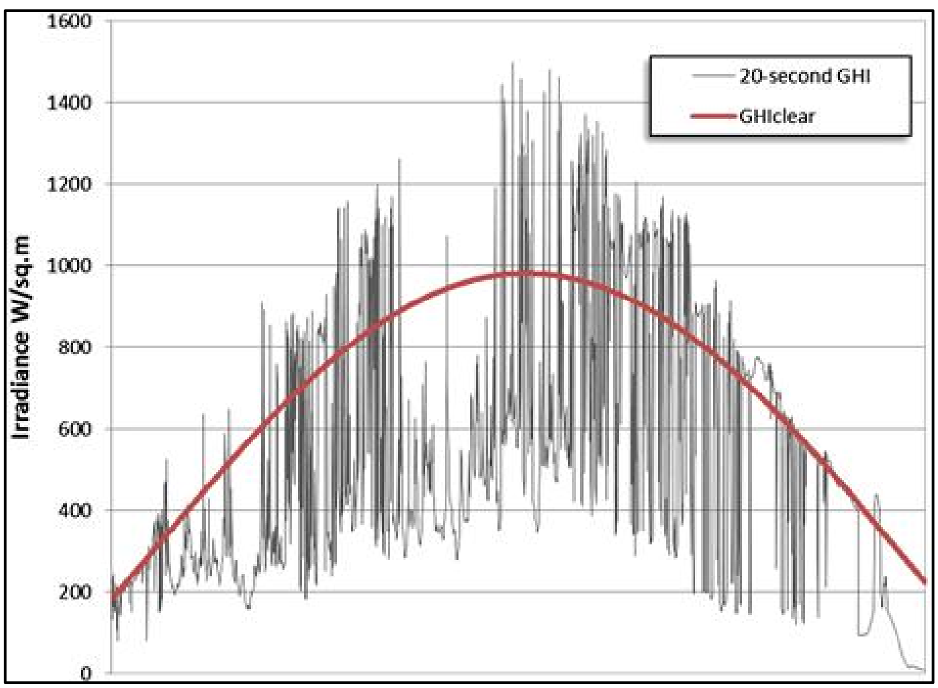

Figure 1. GHI 20-second vs GHI clear (Kleissl et al., 2013, 6.1).

Researchers utilize a wide variety of tools and methods to quantify and decipher fluctuations; however, most efforts begin with solar irradiation data and go on to isolate influencing factors such as location, dispersion, cloud speed, fleet configuration, time interval, and so on. Another term that is often encountered in the discussion of solar variability is "ramp rate." Traditionally, this term was reserved for the description of power plants coming on and offline, or ramping up and down (Kleissl et al., 2013, para. 4). More recently, the wind industry has used the term ramp rate to describe events in which large numbers of turbines suddenly come on or offline in the same manner due to major wind shifts. When observed in the context of solar intermittency events, the term carries nearly the same meaning, although it must be mentioned that the time scale is much shorter and more rapid. Tarroja et al. (2013) considered calculation of ramp rate "the most intuitive measure for quantifying the severity of fluctuations in solar irradiation" (Tarroja et al., 2013, p. 1004). It does serve as an important metric for observing the change in magnitude of irradiation on a surface over a specified time interval, but differentiation must be made between the normal diurnal cycles mentioned earlier and those caused by intermittency events (Tarroja et al., 2013). Time intervals are also an important factor to consider when interpreting data sets. Time resolution plays an important role because at higher resolutions of 1 to 10 seconds, for example, the bi-modal (on and off) nature of solar radiation becomes much more evident (Hoff & Perez, 2010). To express a variation over a particular time interval, researchers often use the term "step change" to express the change in production across a particular time resolution. For example, Golnas and Voss (2010), Golnas, Aghatehrani, and Bryan (2012), and Klima and Apt (2015) all utilized step changes as a variability metric to express the magnitude of fluctuations in various configurations of PV systems. A study by Marcos, Marroyo, Lorenzo, Alvira, & Izco (2010) revealed the extent to which various time resolutions (in this case 1s, 20s, 60s, 600s) affect the magnitude of fluctuations. Several statistical tools can be employed to highlight and characterize the variability of solar resource within a data set containing power or irradiance. Distributions, standard deviations, probabilities, ratios, and various other metrics can be utilized to decipher solar resource variability.

Of particular interest in this research effort, due to its incorporation into the data analysis process, is the Bird Clear Sky Model, authored by Richard Bird and implemented into an Excel® spreadsheet by Daryl Myers. The Bird Clear Sky Model uses a technical report conducted by Richard E. Bird and Roland L. Hulstrom at the Solar Energy Research Institute, entitled *Simplified Clear Sky Model for Direct and Diffuse Insolation of Horizontal Surfaces*, as guidance to compute hourly average solar radiation for every hour of the year, based on 10 user input parameters (Bird & Hulstrom, 1981). The algorithm used in the model produces estimates of clear sky direct beam, hemispherical diffuse and total hemispherical solar radiation on a horizontal surface. For the purposes of this study, only the global horizontal irradiance (GHI), a sum of Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI), was used. This was due to the fact that GHI is the type of measurement taken by the pyranometers on location at the solar farms in Elm City, Fayetteville and Rockingham that comprised the data set for this study. The value of having an hourly clear sky irradiance estimate specific to the desired location, is that a direct comparison between measured and estimated clear sky irradiance can be conducted to assess the variability of the solar resource.

The Dispersion-Smoothing Effect

Many studies have concluded that the combined variability of multiple PV (or wind) generators is less than the variability experienced by a single system (Figure 2) (Wiemken et al., 2001; Lave & Kleissl, 2010, 2011; Golnas & Voss, 2010). These studies, as well as others, suggest

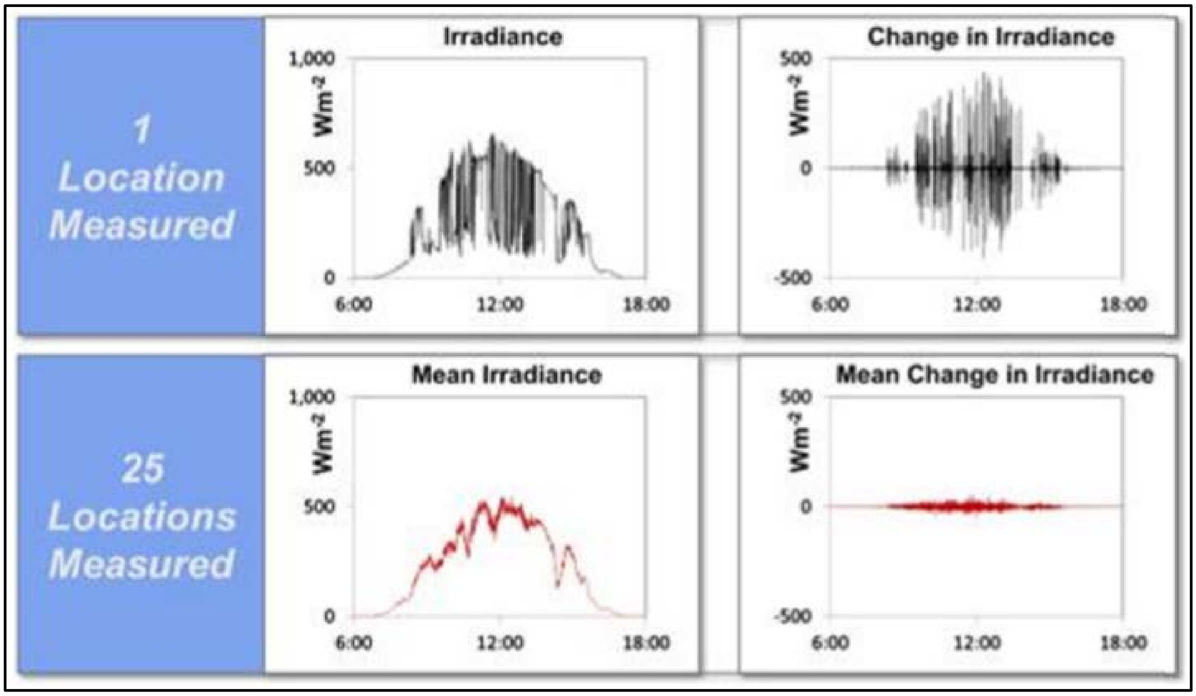

Figure 2. Dispersion-smoothing effect at 25 locations over a 4 x 4 km area (Kleissl et al., 2013, 6.3).

that if two PV generators are placed right beside each other their fluctuations will be almost perfectly in sync and the resulting variability will be nearly equal (Kleissl et al., 2013). Many factors contribute to the behavioral similarity between sites, including distance between generators, the time interval considered, and the speed of clouds passing. Time interval, or resolution, is of interest because high-frequency fluctuations can indicate small, fine clouds, while low-frequency fluctuations can indicate slow-moving formations or even weather fronts. For example, Curtright and Apt (2008) found that even with site diversity of roughly a 280 km range, the PV intermittency among the three sites observed was not sufficiently dampened. They suggested that high, widespread clouds were to blame for the high correlation in power production between geographically dispersed arrays. Although there are instances where even high levels of dispersion fail to reduce the aggregate variability, evidence suggests that increasing the level of spatial diversification reduces the magnitude of fluctuations as a fraction of the total capacity (Tarroja et al., 2013). Wiemken et al. (2001) compiled data from 100 residential PV systems throughout Germany to analyze the effects of aggregate variability as compared to an individual system. Consistent with the many findings that came after, Wiemken et al.'s analysis revealed a considerable decrease in power fluctuations as compared to an individual system (Wiemken et al., 2008).

Groupings of PV generators, sometimes referred to as fleets or ensembles, have been the subject of studies as well. In these instances, the same principles apply in the context of the dispersion-smoothing effect, although attention must be paid to some characteristics of these groupings that affect measures of aggregate variability. Golnas et al. (2012) noted that if within a group of generators a large system accounts for most of the fleet's capacity, that system will dominate the aggregate variability behavior. An earlier study by Golnas and Voss (2010) suggested a similar conclusion, that very large systems negate the smoothing effects of many smaller systems in the same fleet (Golnas & Voss, 2010). Theoretical models have also been created to demonstrate contrasting scenarios of relative output variability. Hoff and Perez (2010) modeled a scenario where 100 MW of PV capacity was distributed in three different ways: as a single 100 MW plant; as one hundred 1 MW plants; and as 20,000 5 kW plants. Relative output variability was found to be 18%, 10%, and less than 1%, respectively (Hoff & Perez, 2010, p. 1792). Within those results it was also determined that variability within the large central plant was largely due to cloud transit speed and dispersion factor, while the distributed systems' variability depended on the number of systems. Although the primary effect of concern remains the same, many underlying factors influence variability.

Relation to Grid Function

Results from this research and other studies that preceded it carry implications beyond just reinforcement that a particular phenomenon exists. High levels of penetration by PV generators influences the operation and function of the electric grid. Additional variable generation must be managed properly by system operators and planners, and therefore any additional knowledge that can assist in strategic development of infrastructure is beneficial. A study conducted by the U.S. Department of Energy found that projections of PV variability for integration studies must be able to model large PV plants, dispersed PV plants on distribution feeders, and the aggregate of all PV plants at time scales of seconds to hours (USDOE, 2009). There are enforceable reliability standards (overseen by the North American Electric Reliability Corporation [NERC]) that have established minimum performance standards (USDOE, 2009, p. 1). These are important for recognizing limits and barriers, but they are not prescriptions for how to mitigate the forces of variable generation. It is, therefore, still largely in the hands of researchers to determine questions concerning power quality and regulation reserves necessary to maintain a reliable electric grid. These issues (power quality and regulation reserves) are necessary when production from a variable resource drops off, requiring that power supply be supplemented by some other form of generation or managed via use of energy storage or changes in demand (known as demand response). The transmission system and dispatchable generators must be able to respond to larger fluctuations if higher penetration of intermittent renewable resources on the grid is achieved. As development of solar projects continues and higher levels of penetration occur, planning for the effects of unpredictable resource variability is vital. For successful integration of PV technology into the grid, "a balanced portfolio of solutions for coping with these imbalances is required on both the supply and demand side" (Perez & Fthenakis, 2015, p. 46).

CHAPTER 3: RESEARCH METHODOLOGY

This research was a quantitative study that utilized several data analysis metrics in an effort to characterize the variability of irradiance and power output from three utility-scale (>1MW) solar farms in North Carolina. These metrics were tools derived from the literature that have been circulated and used widely within the field of renewable energy, and with PV specifically. Beyond the analysis of the measured data, an exploration of a hypothetical "aggregated" generation profile was performed to offer insight into possible mitigation for the problem of resource intermittency.

Overview of Research Design

Historical PV power production data that span a period from January 20th, 2015 to August 1st, 2016 was sampled from three utility-scale installations. Within each month, daily data collected at a 15-minute resolution comprised the sample, with only positive values of AC power generation and corresponding irradiance measurements considered. Data for each location contained two (2) timestamps, one for local time and one for Coordinated Universal Time (UTC); AC power in kW; ambient temperature; horizontal irradiance in Watts/m^2; and plane of array irradiance in Watts/M^2, measured from two pyranometers at different locations on the farm. Within that body of information, this study was concerned with the step changes that occurred between intervals, meaning the differences in values from one 15-minute interval to the next for AC power and irradiance. These changes were assumed to be numerical representations of the variability caused primarily by cloud cover. Step changes had to be critically analyzed to reveal the most significant deviations of the highest magnitude, an analytical process that is addressed in the 'Data Analysis Procedures' section below. Because all the sites possessed corresponding timestamps, an analysis of conditions at various locations within the same geographic region was made. In other words, a measurement of Global Horizontal Irradiance (W/m^2) taken from one location at a particular timestamp, was also taken from a different location at the same timestamp, and any discrepancy indicated dissimilar conditions. Utilization of temperature and plane of array data could benefit future research efforts, but was not be included in this analysis.

Data Collection

Data were collected by an Ecoplexus Real Time Monitoring system powered by AlsoEnergy from the relevant dates of January 20th, 2015 to August 1st, 2016, and were used in this study with explicit permission (see Appendix A). All monitoring hardware was controlled and operated by Ecoplexus. Due to proprietary issues involving non-disclosure agreements (NDAs) between Ecoplexus and shareholders and investors, exact locations of the farms for which data were provided were not disclosed, but were instead named for the nearest municipality. Figure 3 provides a more detailed look at the general locations and geographic dispersion of the farms included in this study.

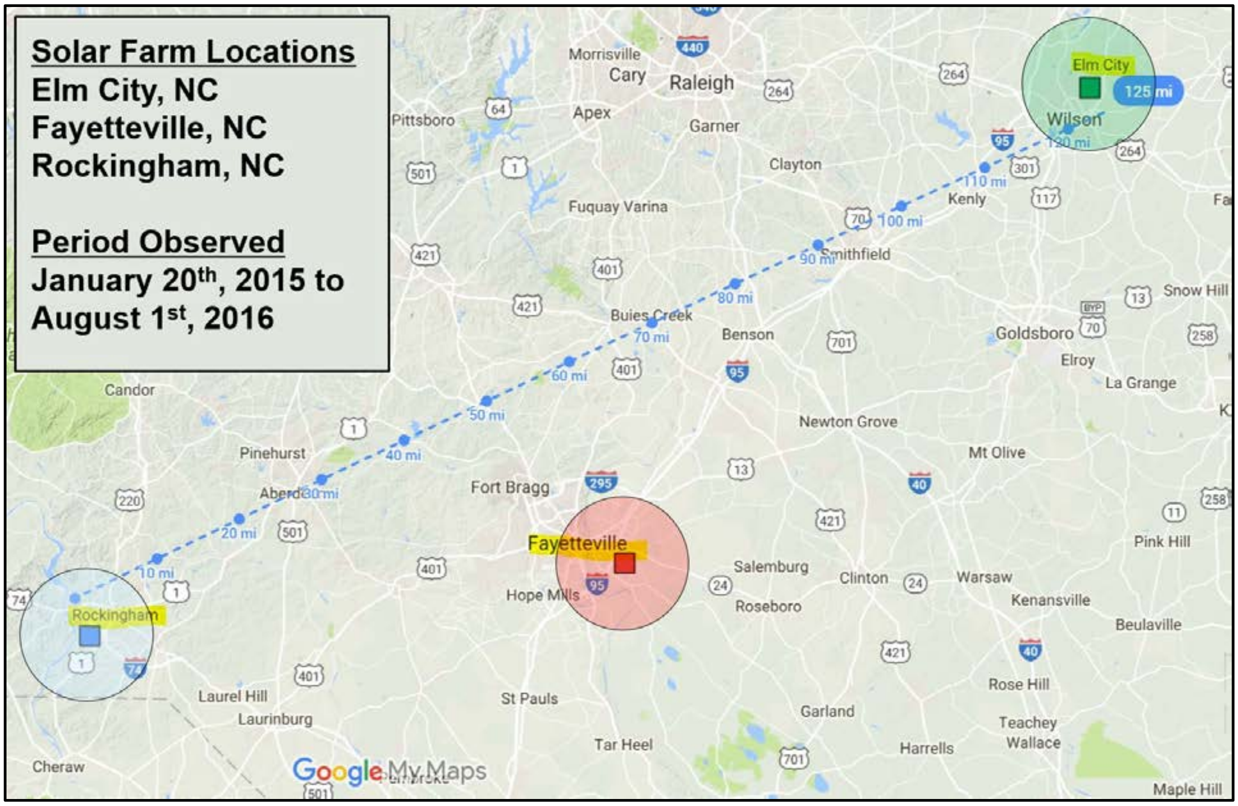

Figure 3. Locations of solar farms included in the study.

Data Analysis Procedures

In order to analyze variation in irradiance across sites, several statistical tests were conducted. Excel was the primary tool used to perform these tests. A number of metrics for observation of variability exist within the field of PV and solar energy, some of which were discussed in the review of literature. Identification of stochastic variability, or variability caused by what statistics would deem a random variable, is not easily accomplished. A preliminary analysis using metrics proposed in a report entitled, *Natural Variability of Irradiance and Power-simple Variability Metrics for Photovoltaic Power Plants,* (Willy, Acker, & Flood, 2014) affirmed that identification of variability in the context needed for this study would prove difficult. This simple metric identifies the standard deviation (σ) of the changes in irradiance (or power) (Δ) and divides that figure into the mean of the sample irradiance (or power). This basic expression of the coefficient of variation in decimal form was intended to identify days of high and low variability. It became apparent, however, that this simple calculation fails to identify the large magnitude fluctuations that occur during highly variable conditions, and would not do for the purposes of this study. Utilization of the Bird Clear Sky Model, adapted by Daryl Myers into an Excel® spreadsheet and authored by Richard Bird, was essential for producing irradiance data to measure against (Bird & Hulstrom, 1981). This model creates a location-specific data set of clear sky irradiance for every day of the year, against which the measured data could be compared. In order to utilize maximum temporal resolution of the data gathered from the solar farms, the hourly data provided by the Bird Clear Sky Model was linearly interpolated to create additional 15 minute time steps between the hourly data that is the model's output. Comparison of clear sky irradiance and measured irradiance requires the use of an algorithm provided by *The Variability Index: A New and Novel Metric for Quantifying Irradiance and PV Output Variability,* authored by Stein, S. S., Reno, M. J., & Clifford, H. W. (2012). This algorithm, pictured in Figure 3, uses the Clear Sky Irradiance (CSI) produced by the model, and Global Horizontal Irradiance (GHI) taken from the measured historical data from the three locations, Elm City, Fayetteville and Rockingham.

$$VI = \frac{\sum_{k=2}^{n} \sqrt{(GHI_k - GHI_{k-1})^2 + \Delta t^2}}{\sum_{k=2}^{n} \sqrt{(CSI_k - CSI_{k-1})^2 + \Delta t^2}} \tag{1}$$

Another similar metric that proved useful in identifying "clear" days (or days that deviated least from the GHI produced by the Bird Clear Sky Model), was the Daily Variability Index (DVI). This algorithm differs only slightly from the Variability Index (VI), as noted in Equation 1.

$$\mathrm{DVI} = \frac{\sum_{i=2}^{n} |\mathrm{GHI}_i - \mathrm{GHI}_{i-1}|}{\sum_{i=2}^{n} |\mathrm{CSI}_i - \mathrm{CSI}_{i-1}|}, \tag{2}$$

Using both the Variability Index (VI) and Daily Variability Index (DVI), individual days were then classified into degrees of variability based on their VI and DVI values, with higher numbers representing days of higher variability. These metrics' (VI and DVI) core purpose is to identify days that contain deviations from the modeled data of the greatest magnitude and highest frequency within the specified interval of time. This can also be conceptualized as the "ratio of the 'length' of the measured irradiance plotted against time, divided by the 'length' of the clear sky irradiance plotted against time" (Stein et al., 2012, p. 2). This means that, provided the clear sky model produces a perfect match to the measured data, VI would equal 1. In a perfect world the modeled clear sky would match the measured clear sky, but more often than not there is uncertainty in the model, which creates slight deviations but still produces values close to one. The effect of time increment, or temporal resolution, must also be addressed because it can drastically affect the magnitude of the VI and DVI as well. Shorter time increments result in higher VI values, therefore reducing its universality and applicability across studies. (Stein et al., 2012, p. 4). Higher temporal resolution data will naturally have more increments, resulting in higher VI sums. Figure 4 offers a useful visualization of the effect of the time increment on mean annual VI. Use of this index alone when classifying varying degrees of variability is not valid without the incorporation of a countering measure, due to the fact that the variability indices can be similarly low during a clear sky day, or an overcast day (Huang et al., 2014). This measure, introduced as the Daily Clearness Index in the report, is created by taking the ratio of measured daily insolation to the daily clear sky insolation provided by the model, and serves to further distinguish the unique conditions that clouds create (Stein et al., 2012, p. 5). This means that Daily Clearness Index is close to one when there are clear sky conditions, and decreases when there is significant deviation from the model.

When these metrics are plotted against one another in a scatter plot form, patterns merge that can reveal particular cloud-cover events, or, of course, the absence of clouds. Variability of individual months was calculated as well, to reveal patterns between locations and to identify months of higher variability. It is worth noting that due to unknown circumstances there were missing data from some of the locations used in this study. To remedy this problem in the analysis of the year 2015, data from the following year (2016) were used in place of missing data to provide a more objective analysis. This prevents skewed averages from occurring when there are excessive zero values in the summation. This is addressed in more detail in Data Validation. When days were classified appropriately, the days of highest variability could be isolated in order to address the research question involving the dispersion-smoothing effect. For this analysis, days of highest variability from each location were analyzed in direct comparison across identical timestamps. This means that when the day of highest variability was identified at one location, that same day was used at the two other locations to analyze the aggregate generation profile. For example, the day of highest variability at the Elm City farm was identified as July 4th, 2015. To perform an analysis of aggregate generation, corresponding data from July 4th, 2015 at the two other locations were averaged and compared.

Using AC power (kW), an average generation profile was created to observe the validity of the claim that the profile will be less volatile in the aggregate (Wiemken et al., 2001; Lave & Kleissl, 2010, 2011; Golnas & Voss, 2010). Creating graphical representations of generation or irradiance profiles provided compelling evidence, in an easy-to-understand format, that reductions in variability do exist.

Although these profiles gave valuable evidence towards proof of concept, a more quantitative tool was necessary to answer the research question regarding the smoothing effect. To assist in this effort, incorporation of ramp rate was included for further affirmation. In the context of this study, ramp rate is defined as the change in power output of the solar farm or irradiance sensor over two consecutive periods of the duration (Δt), which is 15 minutes for this data set (Haaren et al., 2012).

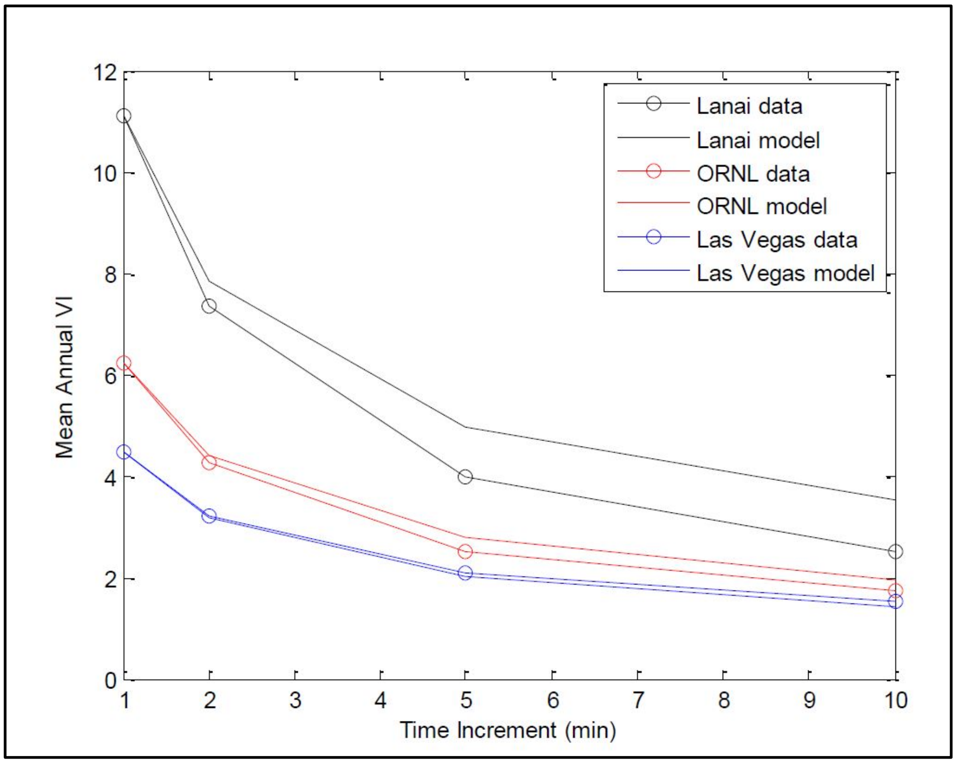

Figure 4. Effect of time increment on mean annual VI (Stein et al., 2012, p. 5).

Because the Variability Index seeks to identify the highest quantity of high magnitude changes in irradiance over the 15 minute Δt, it follows that extreme changes in power output observed in ramp rates would serve to affirm the findings of the VI. It must be noted that time step is a significant factor affecting the size and context of ramp rates. Ramp rates calculated at short time steps will for the most part be smaller than those calculated at longer time steps.

From an industry perspective, a 15 minute time step, or Δt, represents an above-average length of time, and will therefore result in ramp rates of higher values. This is because they will simply have more time over the course of the 15 minutes to deviate from the previous value. Understanding the distribution of ramp rates is important for identifying the most extreme cases, which most often represent the scenarios of most importance to grid-operators and researchers. Although both positive and negative ramp rates are significant, similar trends and impacts can be seen between both, therefore justifying the plotting of the absolute value (Kleissl, J., 2013). Attention was paid to negative ramp rates for the purposes of this study, but the majority of distributions were plotted using only the absolute value.

The most practical statistical tool for ramp rate assessment is the cumulative distribution plot, which allows for the extreme percentiles (such as 95^{th} and 99^{th}) to be identified and used as a source for comparison. The most notable comparison made in this study was the difference in ramp rate distributions between a single site such as Elm City, and the aggregate generation of all three sites. These cumulative distribution plots also allowed for observation of probabilities that a particular ramp rate will occur, which offered further affirmation to the claim that generation will smooth when observed in the aggregate.

CHAPTER 4: RESEARCH FINDINGS

Data Validation

To accomplish the most complete analysis of the measured data set spanning January 20th, 2015 to August 1st, 2016, the data were consolidated to a single year, and missing data replaced with existing data from the same day of the next year. For example, February 17^{th}, 2015 to February 19^{th}, 2015 at the Fayetteville site was missing irradiance and power data, and was therefore replaced with data from the same dates in the 2016 data set. There were several other instances where this became necessary, with the final product resulting in a year of complete data values for irradiance and power.

Key Characterizations and Findings

This research was guided by three research questions, the first of which was: What is the variability of Global Horizontal Irradiance (W/m^2) at all three sites included in this analysis? After analysis of the three locations included in the study (Elm City, Fayetteville and Rockingham), the results revealed that the sites exhibit very similar patterns of variability. Given their proximity, this finding is to be expected. To better understand the distributions presented in the scatter plots, general areas were assigned conditions to better conceptualize the distributions of the Variability Index (x-axis) and Daily Clearness Index (y-axis). Because these products of analysis are not necessarily statistical findings, it is best to label them as key characterizations that help better understand the ultimate conclusions. For each of the four conditions described (clear, overcast, mild variability all day, and high variability all day), one day is highlighted whose characteristics best represents its respective condition.

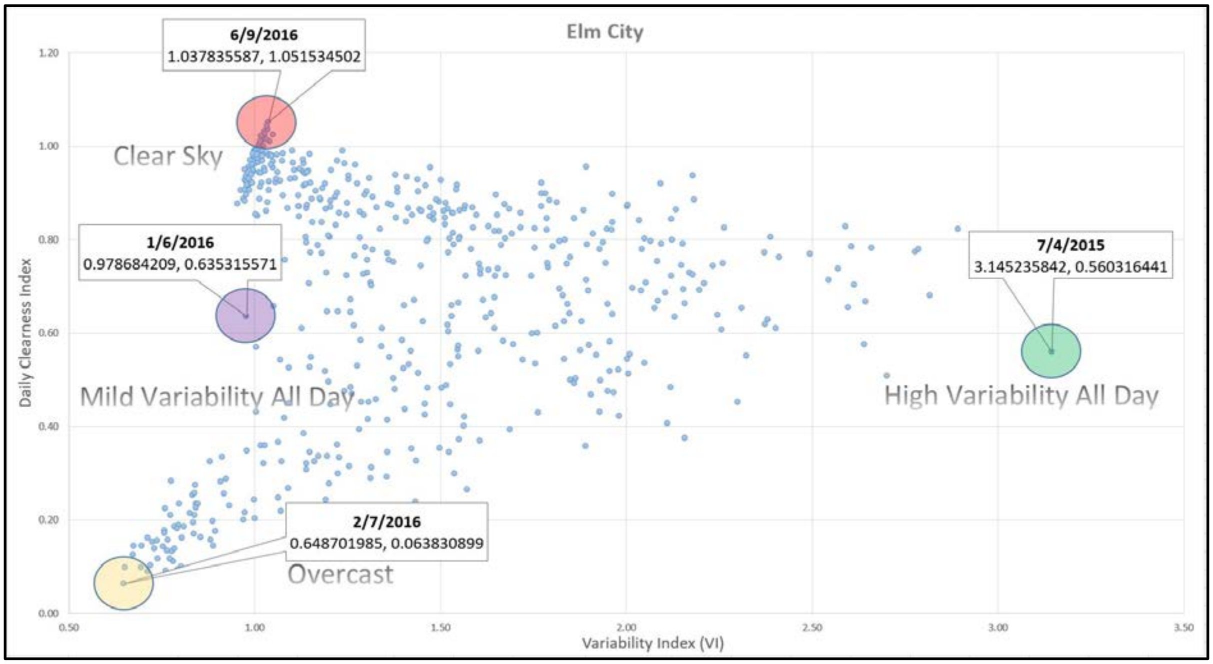

Figure 5. Elm City scatter plot, 1/20/15 to 8/1/16.

Data in Figure 5 illustrate the whole spectrum of variability for the entire period observed at Elm City (January 20th, 2015 to August 8th, 2016), with each dot representing a day within that time span. The various colored circles highlighting a day at the fringe of each margin, are representative of a particular condition, with surrounding dots exhibiting similar irradiance profiles. Two dots along the x-axis with a value of "1" are highlighted for the purpose of illustrating the need to include a Daily Clearness Index. Without a corresponding index, there would be no statistical difference between the days according to the Variability Index between those two highlighted days, which are represented in Figures 5 and 6 by the red and yellow colors. Although as the profile in Figure 8 clearly demonstrates, their actual behavior is quite different.

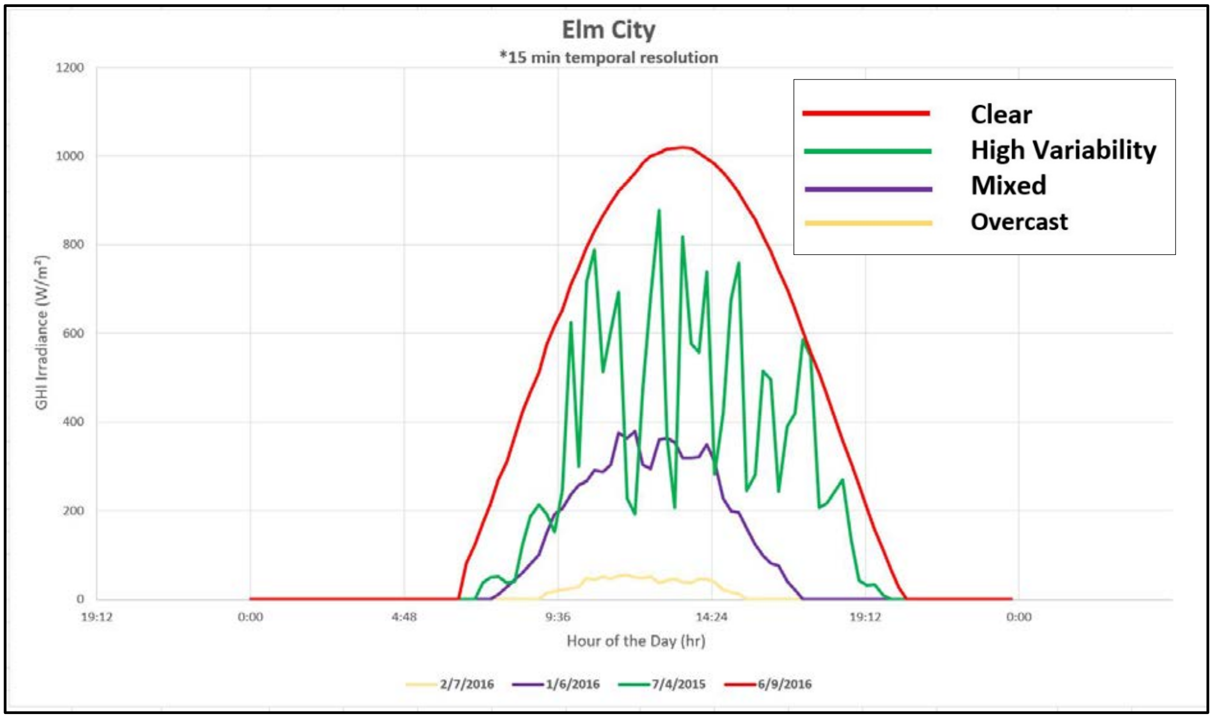

Figure 6. Elm City with profiles corresponding to Fig. 4 (GHI (W/m^2) vs Hour of the Day (hr)).

The red dot in Figure 5 and red line in Figure 6 illustrate a clear sky day, indicative of no cloud cover and fairly uninterrupted irradiance. The yellow dot in Figure 5 and yellow line in Figure 6, conversely, represent sustained cloud cover with very low irradiance reaching the pyranometer. The VI is able to recognize dramatic shifts in irradiance measurements between relevant time steps, which neither the red nor yellow have exhibited. However, it becomes apparent when viewing their daily profiles that their difference is substantial. It is for this reason that the Clearness Index was included in the analysis.

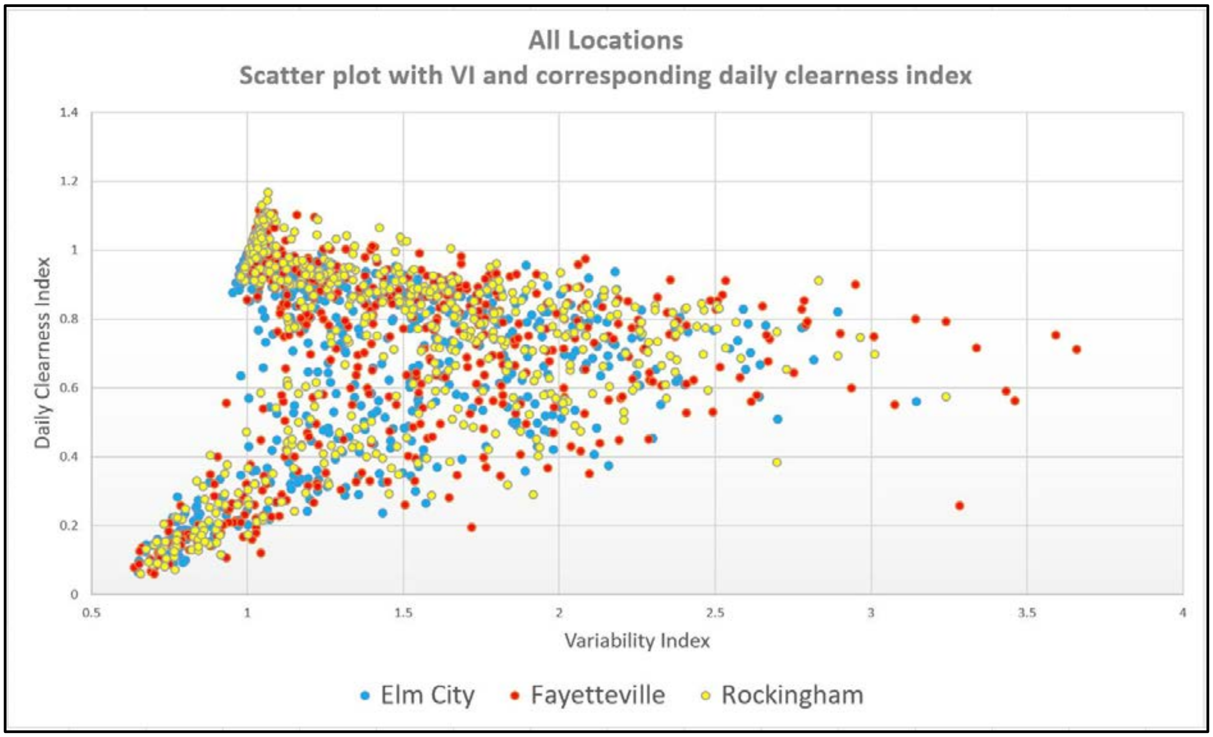

Figure 7. Cumulative scatter plot (all locations).

Through observation of the cumulative scatter plot seen in Figure 7 it is obvious, given their similar profiles, that all locations exhibited similar conditions in terms of irradiance patterns. This conclusion is to be expected considering their relatively close geographic proximity (<125 miles). Another beneficial observation can be found in the seasonal breakdown of VI, for identification of the months of highest variability. Here (Figure 8), winter was defined as December to February, spring as March to May, summer as June to August, and fall as September to November. Daily averaged VI was included for every site for 2015, with missing data substituted from following year (2016) on the same day when necessary. Figure 8's area chart reveals a high concentration of clear days (or low VI) in the winter and fall, with days of higher variability more frequent in the spring and summer. This suggests the presence of high frequency, high magnitude shifts in irradiance due to passing clouds in the months spanning March to August.

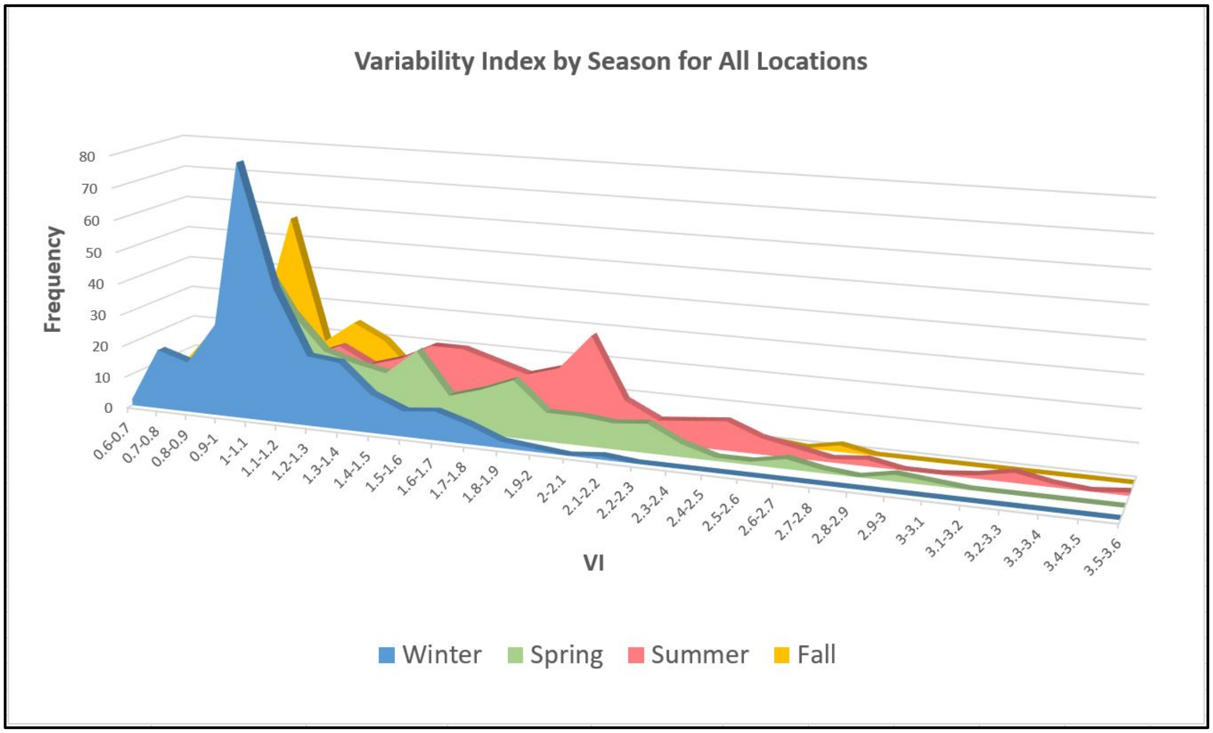

Figure 8. Area chart of VI frequency by season (all locations).

Another perspective can be offered by observing the monthly mean VI for the year 2015 (once again missing data replaced with existing data from following year). Figure 9 clearly shows a strong correlation amongst individual sites, with some deviation in late summer at Fayetteville which exhibited higher variability as compared to the remaining two sites. Further breakdown of site specific variability can be found in Appendix B.

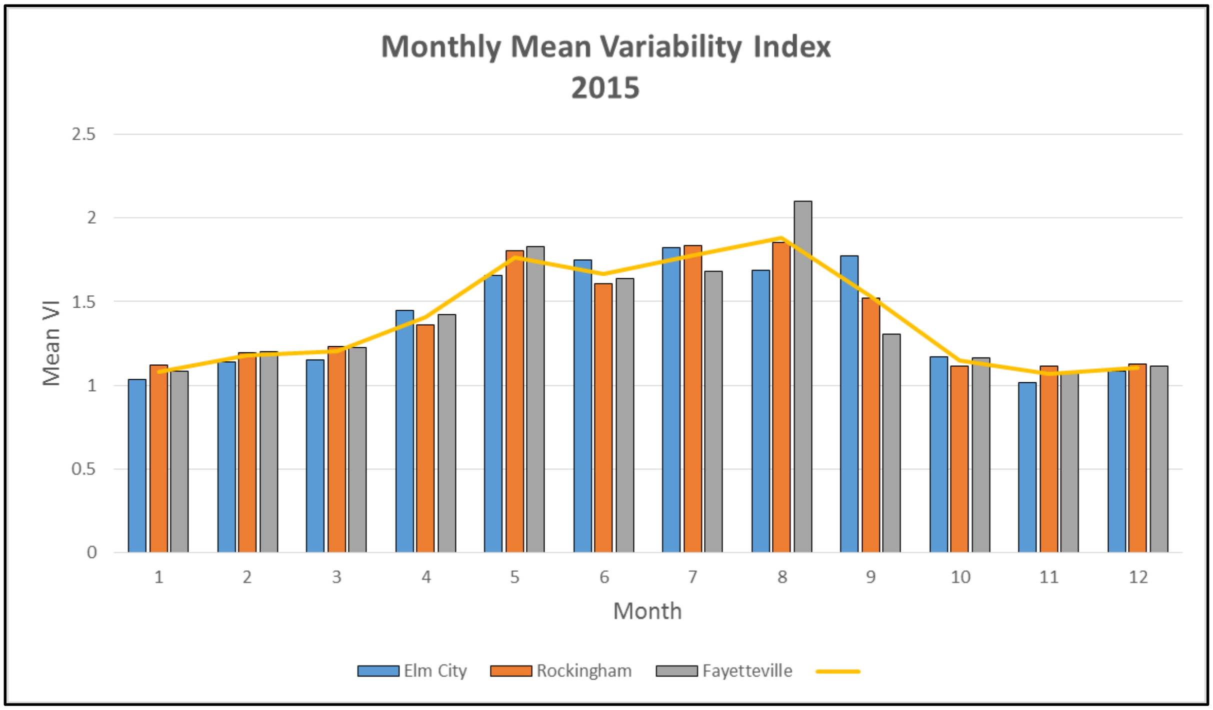

Figure 9. Average VI by month (all locations).

What remains to be seen is whether or not this geographic proximity limits the smoothing of the generation profile when observed in aggregate. This could suggest that short timescale cloud events are isolated enough that simultaneous production at a nearby location could compensate for temporarily volatile conditions. Through analysis of irradiance variability, the most extreme days were identified and isolated to perform an analysis regarding the dispersion-smoothing effect. The day of highest variability at Elm City, NC, was identified as July 4th, 2015 (Figure 10). This product of analysis is included in this chapter as a means to characterize an individual site whose behavior may provide a necessary transition to later findings. Here, a useful juxtaposition between Figures 10 & 11 reveals a dramatic shift in behavior when the measured sites were averaged that must be affirmed quantitatively.

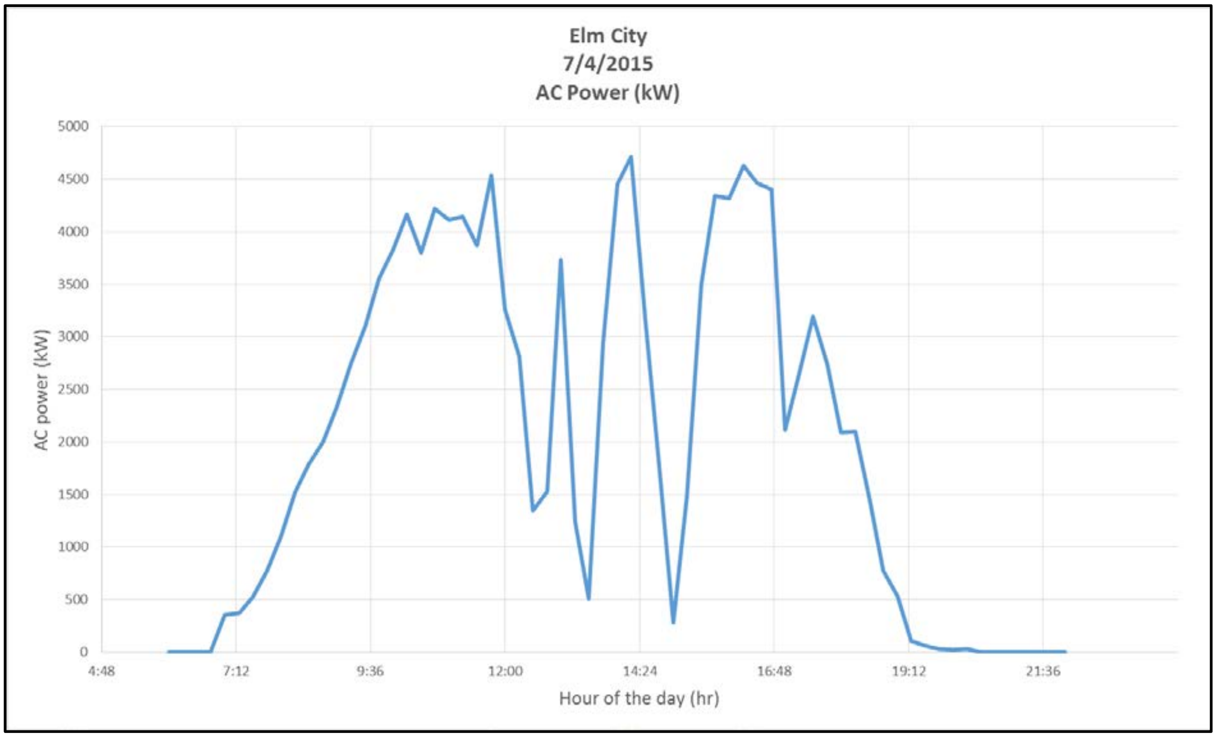

Figure 10. Elm City, NC July 4th, 2015 AC power (kW) generation profile.

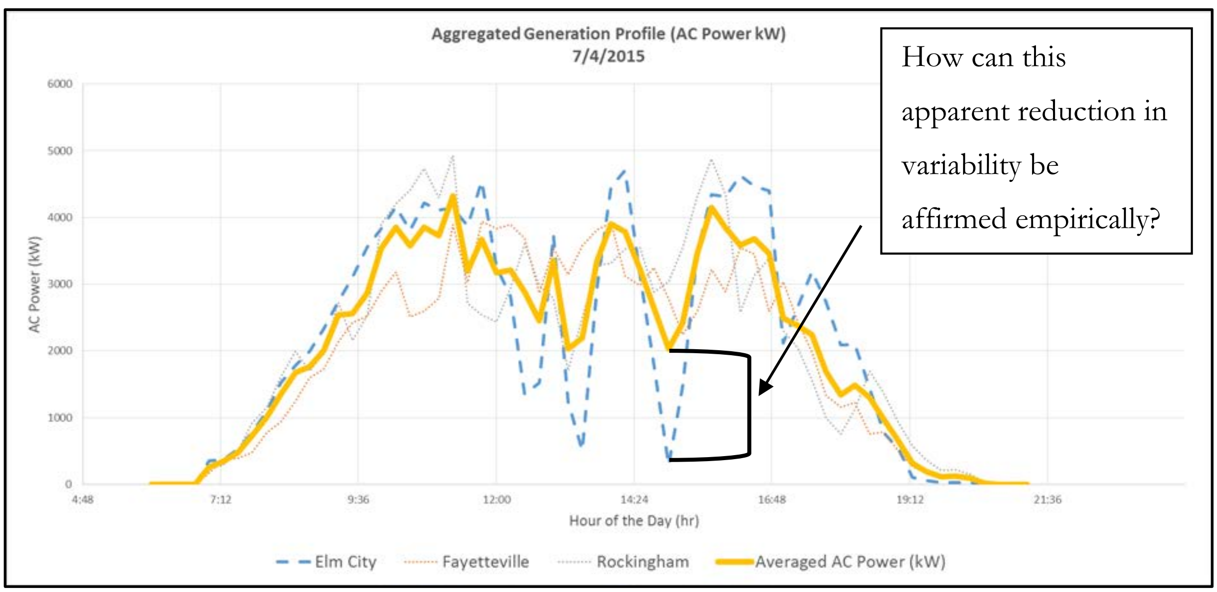

Figure 11. Elm City, NC July 4th, 2015 aggregated AC power (kW) generation profile.

As highlighted in Figure 11, there seems to be a significant reduction in the volatility exhibited in the original generation profile in Figure 10. This would suggest that the level of geographic dispersion amongst the three locations does prove adequate to benefit from the dispersion-smoothing effect. To further explore the reduction in ramp up/down events as noted in Figure. 11, a more thorough analysis of ramp rates and their relation to the generation smoothing followed.

Ramp rates within the context of this study were defined as the changes in power output (AC kW) of the solar farm over two consecutive periods of the duration Δt, which is 15 minutes in this case. A specific example of the dispersion smoothing effect was explored in Fig. 11, which graphically displayed the day of highest variability at Elm City (July 4th, 2015), with the aggregate generation profile interposed to highlight the reduction in ramp rate magnitude.

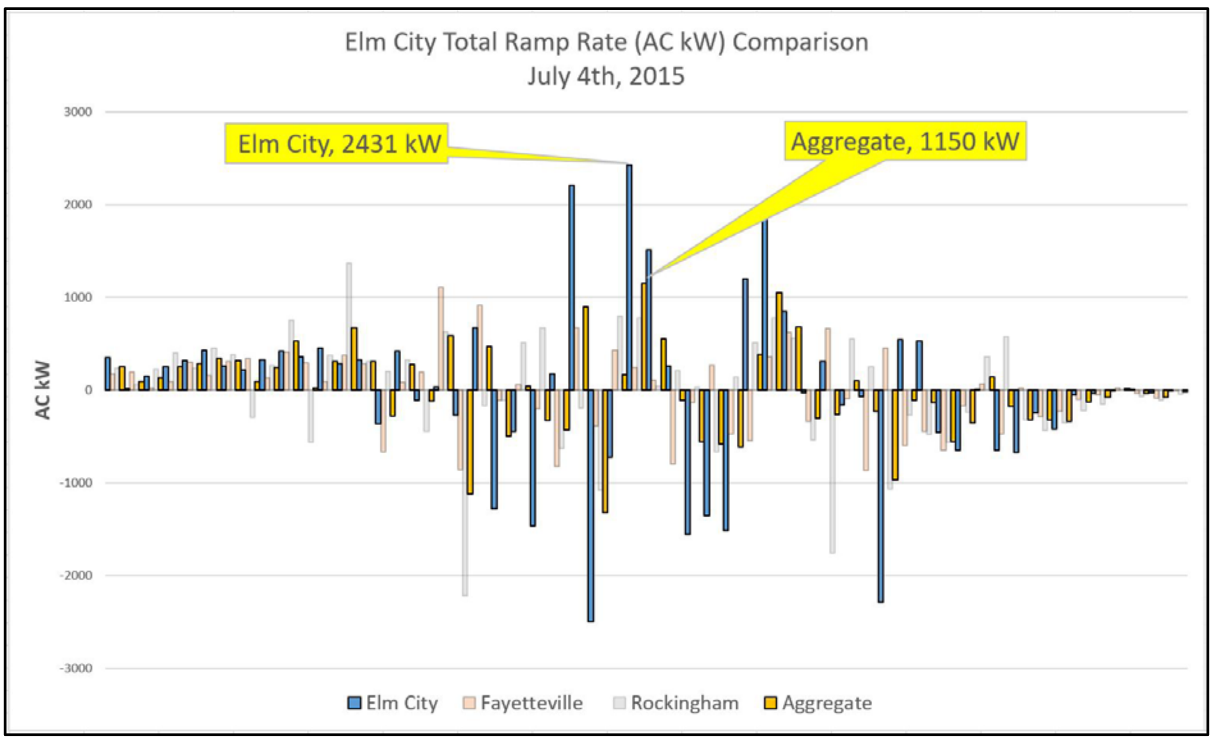

Figure 12. Elm City, NC July 4th, 2015 ramp rate comparison.

Figure 12 shows the reduction of the highest positive ramp rate on July 4th, 2015 reduced from 2,431 kW at the single site (Elm City) to 1,150 kW when observed in aggregate. A proportional reduction of the most negative ramp rate (≈47%) can be seen in the ramp down side as well.

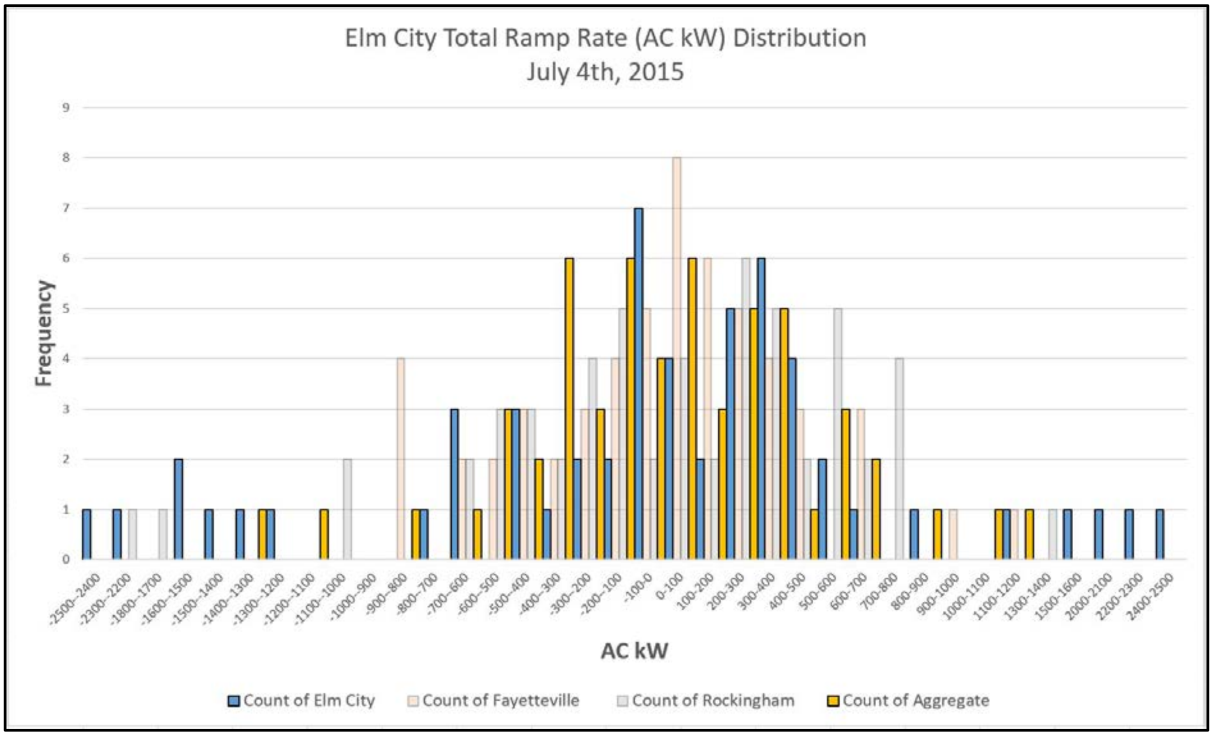

Figure 13. Elm City, NC July 4th, 2015 ramp rate distribution.

Further affirmation of the reduction in ramp rate magnitude on July 4th, 2015 in Elm City can be seen in the Figure 13 histogram, which displays the frequency of various ramp rates in 100 kW bins. The concentration of the aggregate ramp rates is drawn in from the peripheral, indicating a higher occurrence of low magnitude ramp rates of between -500 and 500 kW, whereas the ramp rates at the single site (Elm City) continue to the outer edges, indicating the presence of higher magnitude ramp rates reaching (+-) 2500 kW. There are ten instances of ramp rates at the Elm City site exceeding the highest recorded ramp rates of the aggregate generation profile. It is evident from the Figure 13 histogram that the aggregate generation concentrates ramp rates in the smaller bins, with a much higher frequency of low magnitude ramp rates. This confirms the smoothing of generation in the aggregate for the day of highest variability (July 4th, 2015) at Elm City, although attention must be paid to the entire time observed in this study. To perform an analysis on the entire scope of data, insight was derived from cumulative frequency distribution plots.

Cumulative frequency is useful for identifying the number of observations that lie above (or below) a particular value in a data set. For example, the cumulative distribution of 15 minute ramp rates shows that ramp rates larger than 3000 kW/Δt have a 20% probability of occurrence, but ramp rates larger than 5000 kW/Δt almost never occur. This becomes useful for comparison between the measured data from the three sites and the aggregate generation profile, to identify how the magnitude of ramp rates has shifted. Before continuing, attention must be paid to the use of absolute value in the cumulative frequency plots created in this analysis. Aside from being common practice in research of this kind, use of absolute value can also be justified empirically by observing the symmetry found in the positive/negative ramp rate distributions for the entire data set. Figure 14 clearly shows this symmetry, thus clarifying the use of absolute value throughout the remainder of this report.

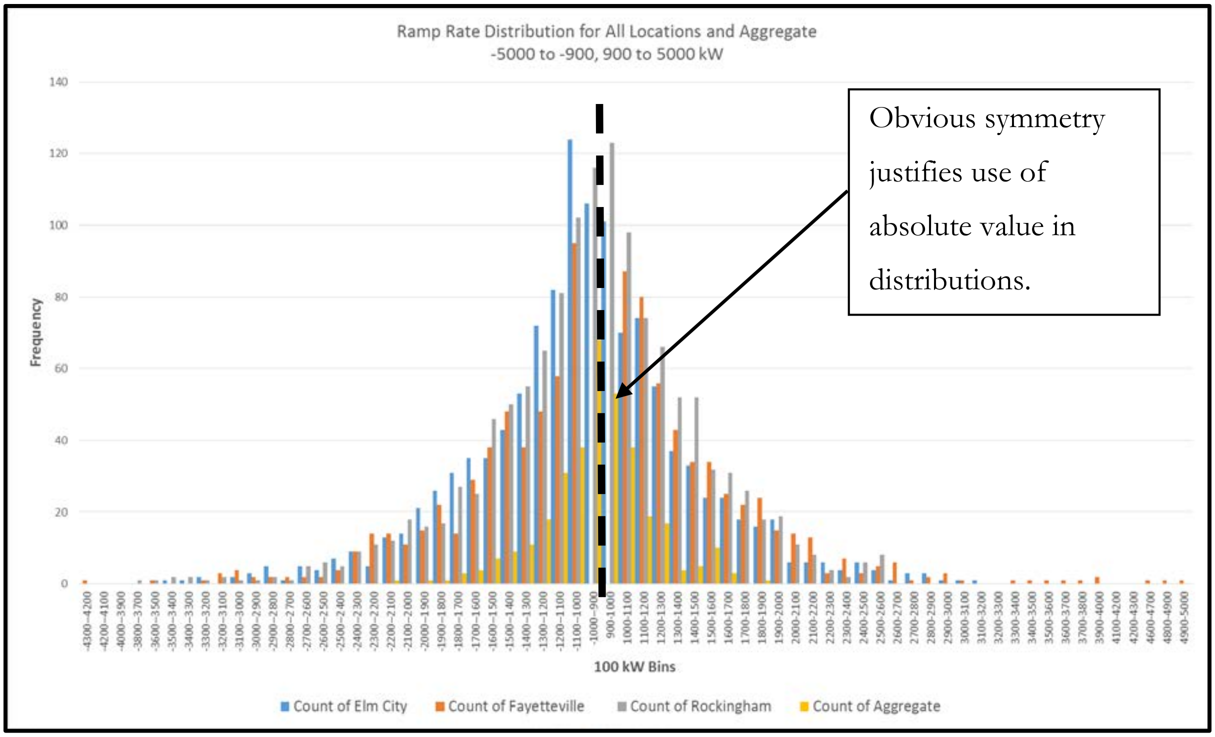

Figure 14. Positive/negative ramp rate distribution for entire data set.

Figure 15 displays the cumulative frequency for Elm City, Fayetteville and Rockingham's absolute ramp rates at 15 min time steps.

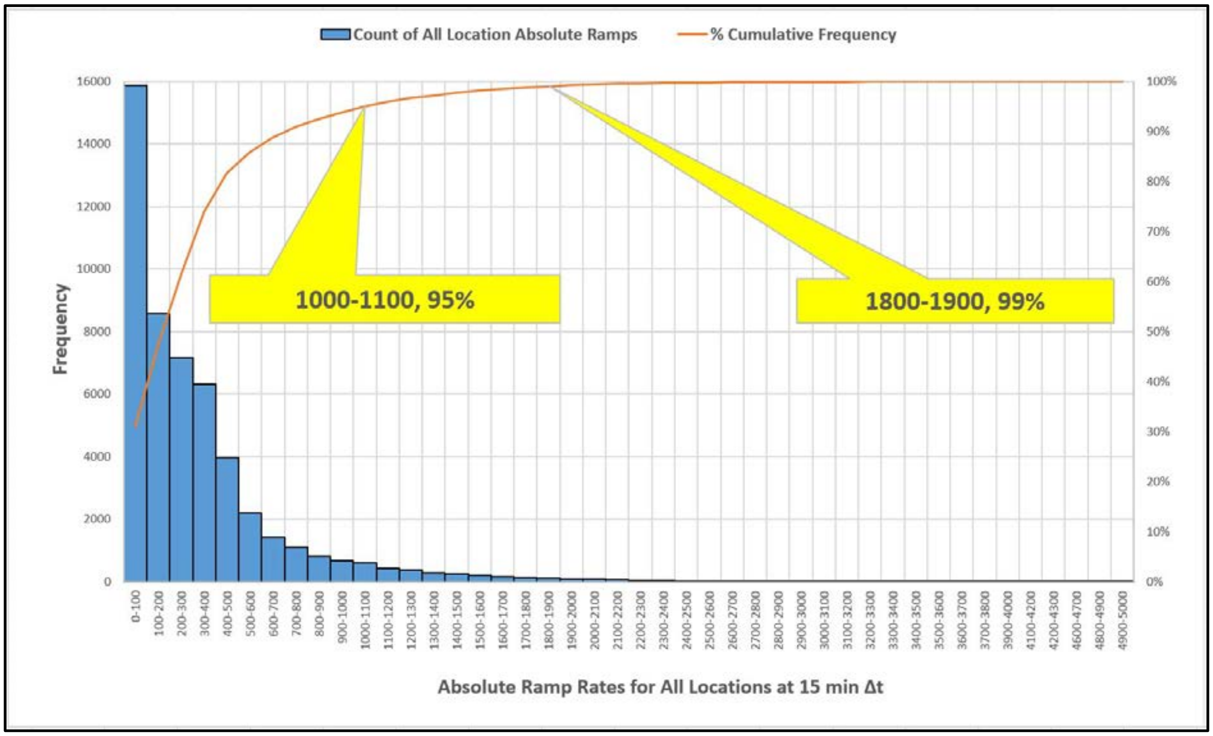

Figure 15. Cumulative frequency distribution for all location's measured data.

As the plot indicates, there is a wide range of ramp rates for the time observed, the highest of which was 4,923 kW at the Fayetteville location. It can also be seen that 99% of ramp rates are less than 1,900 kW, with an only 1% chance of occurrences over 1,900 kW. Figure 16 displays the cumulative frequency for the aggregate generation only, therefore containing only 17,864 values as compared to the 51,307 values contained in the cumulative plot for all sites included in the study.

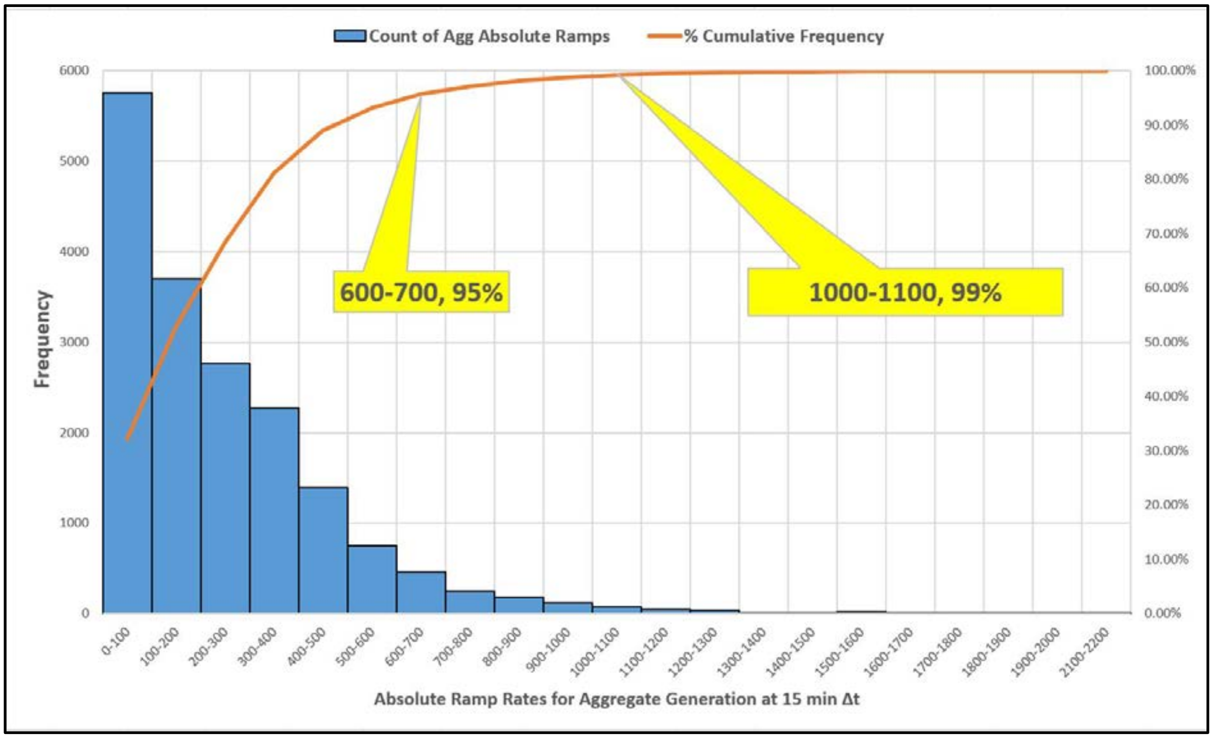

Figure 16. Cumulative frequency distribution for aggregate profile.

As Figure 16 indicates, 99% of ramp rates for the aggregate generation are less than 1,100 kW, with a maximum ramp rate of 2,127 kW. It must also be noted that 95% of the aggregated ramp rates are less than 700 kW, with only a 1% chance of a ramp rate above 1,100 kW, contrasted with a 5% chance of a ramp rate occurrence higher than 1,100 kW for the measured data set. Comparison of these frequency distributions indicate a significant reduction in ramp rate magnitude for the aggregate generation, with a much higher chance of large magnitude ramp rates occurring at the individual sites.

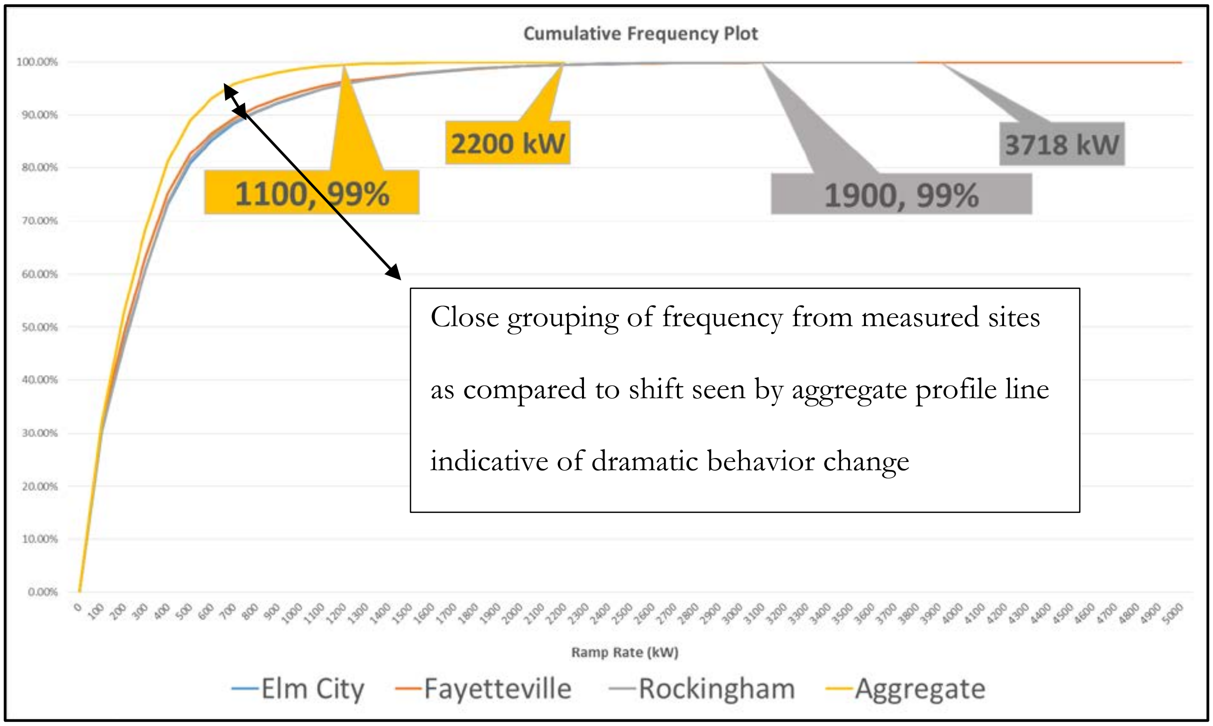

Figure 17. Cumulative frequency plot of all locations including aggregate profile

The cumulative frequency plot in Figure 17 provides the most obvious visualization of the shift of ramp rate behavior. It is evident by the close grouping of the measured sites (Elm City, Fayetteville and Rockingham), that these sites have very similar ramp rate patterns. The deviation by the aggregate line inwards shows a tendency towards lower magnitude ramp rates, occurring more often. Rockingham's statistics are highlighted in grey because out of all the three measures sites, Rockingham contained the lowest, of the highest measured ramp rates. Even at its position as the lowest of the three, the highest ramp rate in the aggregate profile still exhibited a 42.8% reduction.

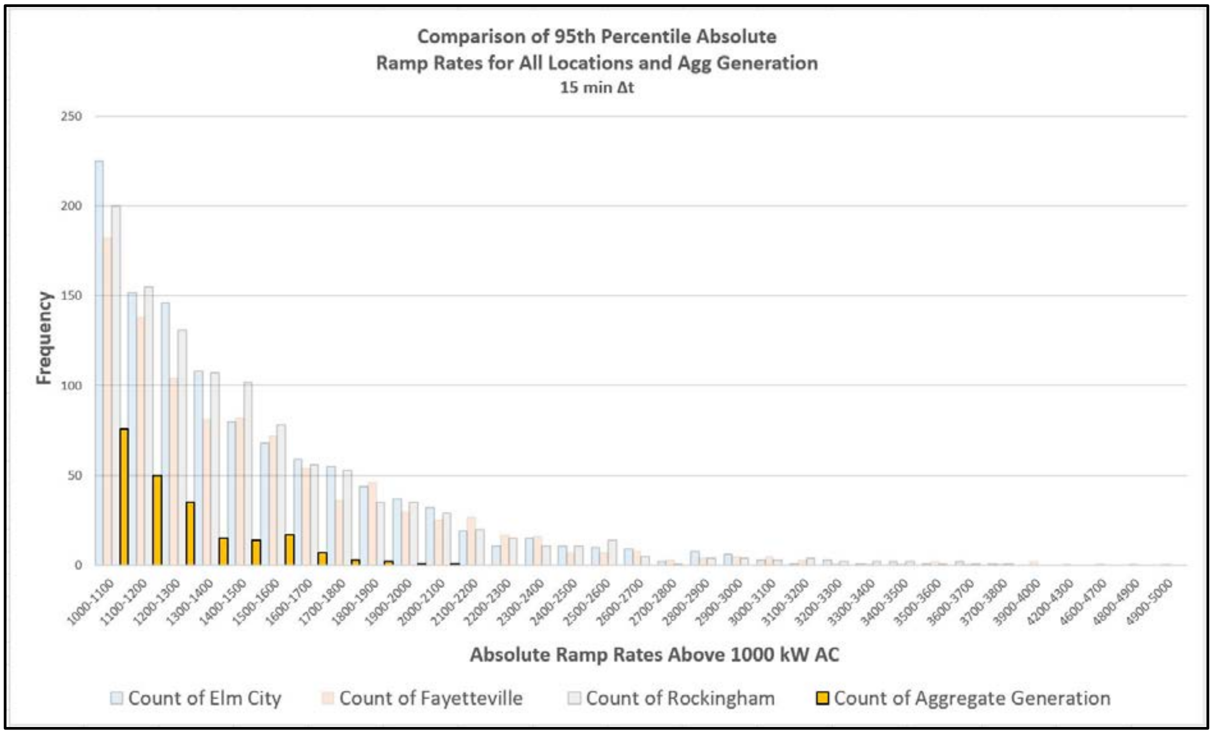

Figure 18. Histogram of absolute ramp rates in 95th percentile (all locations).

In order to gain a better perspective for the 100 kW bins that are dwarfed by the high frequency of low magnitude ramp rates (0-500 kW), a closer look was taken, as shown in Figure 18, of the top 5% ramp rates for all sites. The resolution of Figure 18 allows for closer insight into the direct comparison between the three sites and the aggregate generation profile. It is apparent that beyond ≈2000 kW, there is still a high ramp rate count for all locations except that of the aggregate generation.

Table 1 offers the most concise summary of the key findings. Perhaps the most revealing statistic is found in the row that displays the percentage of ramp rates that fall at or below the 500 kW threshold. This threshold was identified as being 10% of the nameplate capacity (5 MW) of the farms included in this study. Nearly 90% of ramp rates in the aggregate generation profile fall below that low magnitude, 500 kW, threshold. It must be noted that if the aggregate generation profile is treated as a combined site, its nameplate capacity would technically stand at

15 MW, meaning 10% of nameplate capacity would be 1,500 kW. Although the theoretical capacity changes, the fact remains that there is a significant decrease in the presence of high magnitude ramp rates, with the vast majority concentrating below 500 kW.

Table 1. *Summary of Findings from Cumulative Frequency Distributions*

	Elm City	**Fayetteville**	**Rockingham**	**Aggregate**
<99th Percentile	2000 kW	1900 kW	1900 kW	1100 kW
<95th Percentile	1200 kW	1100 kW	1200 kW	700 kW
≤ 500 kW	80.81 %	82.68 %	81.60 %	88.96 %
Max Ramp (+-)	4265 kW	4923 kW	-3718 kW	-2127 kW

Note. Percentile rows refer to ramp rates below designated threshold, for example at Elm City, 99 percent of ramp rates are below 2000 kW.

CHAPTER 5: CONCLUSIONS AND DISCUSSIONS

Solar variability was characterized over 1.5 years at three individual 5 MW solar farms that are sited approximately 125 miles apart at the longest point. Global Horizontal Irradiance (GHI) measurements (W/m^2) were recorded at a single point at each site with a pyranometer, along with power output (kW AC), both at a 15 minute temporal resolution. Using the Variability Index (VI) and the Clear Sky Index (CSI), quantification and distribution of variability was developed to profile the behavior of the individual sites. Using the scatter plot, various conditions (Clear, Overcast, High Variability, Mild Variability) were assigned to individual days, allowing for characterization by location. In reference to the first research question, it was determined that Elm City, Fayetteville and Rockingham, North Carolina, all exhibit similar behavior in regards to the variability experienced throughout the sampling period, which is to be expected when considering their geographic proximity. Although a larger sampling of locations perhaps could have provided a more complete profile of variability within North Carolina as well as a more pronounced effect from site aggregation, its scarcity did still offer a unique perspective into the second research question which dealt with the dispersion-smoothing effect.

The second research question asked what effect an aggregated generation profile of all three locations would have on variability of power output. Due to the limited number of sites included in the research, and the fact that their locations are not widely dispersed (<125 miles), determining the extent to which variability is reduced became a question of great interest. Classification of varying degrees of variability addressed in the first part of the research, allowed for the identification of days of highest VI. July 4th, 2015 was identified as the day of highest variability at Elm City. Using this single day, an aggregate profile was created using temporally corresponding data points for AC power (kW). Graphically, it was revealed that a significant reduction in ramp rate magnitude had taken place. Continuing on to an analysis of ramp rates led to the discovery that the reduction in variability extended beyond just the single day at Elm City, and applied to all locations across the entire sampling period. Using cumulative frequency distributions and histograms, I determined that the occurrence of high magnitude ramp rates dropped significantly in the aggregate AC generation. This finding offers evidence that the dispersion-smoothing effect can have profound impacts to the issue of resource intermittency, even at distances smaller than 125 miles.

Lave et al. (2010) conducted a study using four solar sites in Colorado, in which solar irradiance was averaged and ramp rates were compared to the individual sites in an effort to observe the smoothing effect. Much like my research, this study sought to quantify the effect of an aggregate (or average) profile as compared to the behavior of an individual site. Ramp rate analysis revealed a significant decrease in the mean ramp rate magnitude, maximum ramp rate magnitude, standard deviation and kurtosis of the average compared to each individual site. Overall, there was a 23-51% decrease in the ramp rate that has a 5% probability of occurring for the aggregate generation profile (Lave et al., 2013, p. 2872). Use of cumulative distribution analysis in my study allowed for direct comparison, which revealed a 36-41% decrease in the ramp rate that has a 5% probability of occurring for the aggregate generation profile. The only distinction that must be pointed out is that Lave et al. used irradiance ramp rates, as opposed to power, but in this particular comparison, irradiance is a suitable proxy. In both cases, the resulting conclusion revealed smaller ramp rates and less uncertainty in grid-operation, thus reducing the need for expensive ancillary services or spinning reserve.

Further research would be beneficial for determining the precise limitations of using lower temporal resolution data, such as the 15-minute resolution used for this study. It is possible that there is significant underestimation of variability that is not captured using a 15 min time scale. Continued development of metrics such as VI and CSI will be of great interest to future research for their ability to potentially predict ramp events and more successfully mitigate their detrimental effects. Using techniques demonstrated in this research that allowed for the variability classification of a particular site could be expanded to a forecasting tool. Within this study, I was able breakdown seasonal, monthly, daily and even hourly variability scores. To expand the utility of these numerical assignments, future research could pair these data with meteorological information to assess its accuracy as well as its ability to forecast periods of high variability, and ultimately the need for ancillary services that would be necessary to mitigate the adverse effects that result from variability caused by weather events. If, for example, a utility was able to identify a range of days at the Elm City site that possess, historically, a high VI score and that utility could successfully predict the need for spinning reserves or adequate storage to offset a high magnitude power fluctuation, the VI tool would prove itself invaluable.

Another possible direction to continue this research effort could be identification of a conversion factor to be used when converting irradiance data to ultimate power output. Although there are several modeling systems that are used in the market today that developers use to estimate power output from geographic locations, few factor in the detailed effect of resource variability that this research explores. Using measured irradiance data, which are available in abundance through organizations such as the National Renewable Energy Laboratory (NREL), and pairing that data with measured power data, which is harder to acquire due to proprietary issues, a conversion factor to estimate potential production could be created. Due to the fact that variability observed by a point measurement, such as those taken by a pyranometer that measures GHI, does not correspond fully to the variability of the entire plant due to the smoothing that takes place within the area of the plant, a conversion factor is needed to include these factors. This study contains irradiance and power data from three individual sites, therefore allowing a researcher to cross verify a conversion factor with three different sources and produce an accurate factor, useful to developers, utilities and the research community alike.

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APPENDIX A

Informed Consent Letter

Appalachian
STATE UNIVERSITY
BOONE, NORTH CAROLINA 28608

To Whom It May Concern (at Ecoplexus Inc./Carolina Solar Services),

I am writing to request access to archived performance data (in any form it may be available) from your company's portfolio for my (Jakob Sjostrand) individual research efforts at Appalachian State University (Boone, NC). I intend to use the data towards the completion of a Master's Thesis regarding the development and proliferation of utility scale solar within the state of North Carolina. Any data acquired will be used solely for educational purposes. Details regarding exact locations of sites will be generalized to a nearby city or town so as to not make that information public. Anonymization of any other data acquired can be done so as instructed.

Your approval would be greatly appreciated.

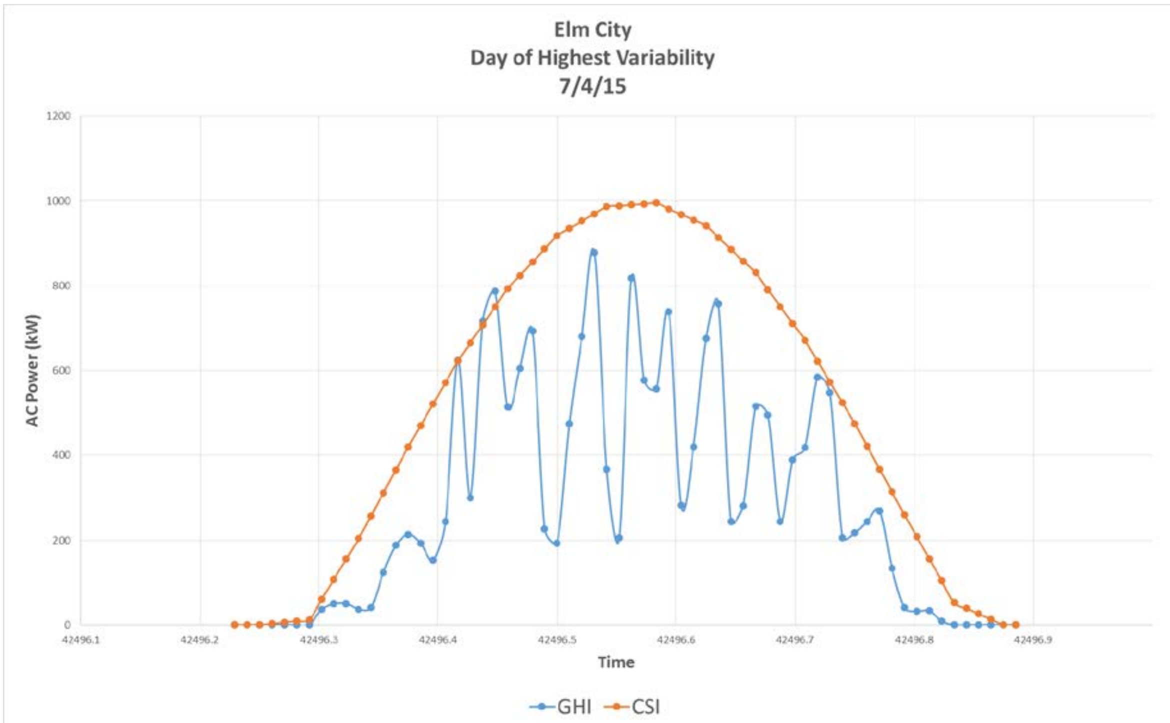
Sincerely,

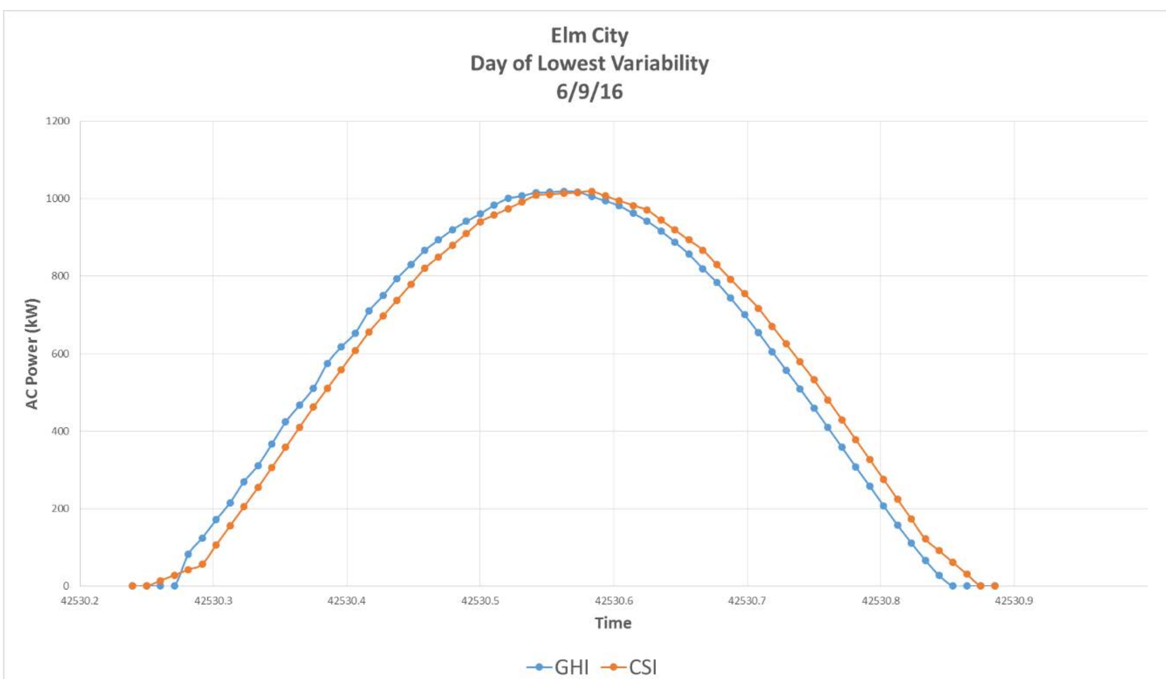
Jakob Sjostrand

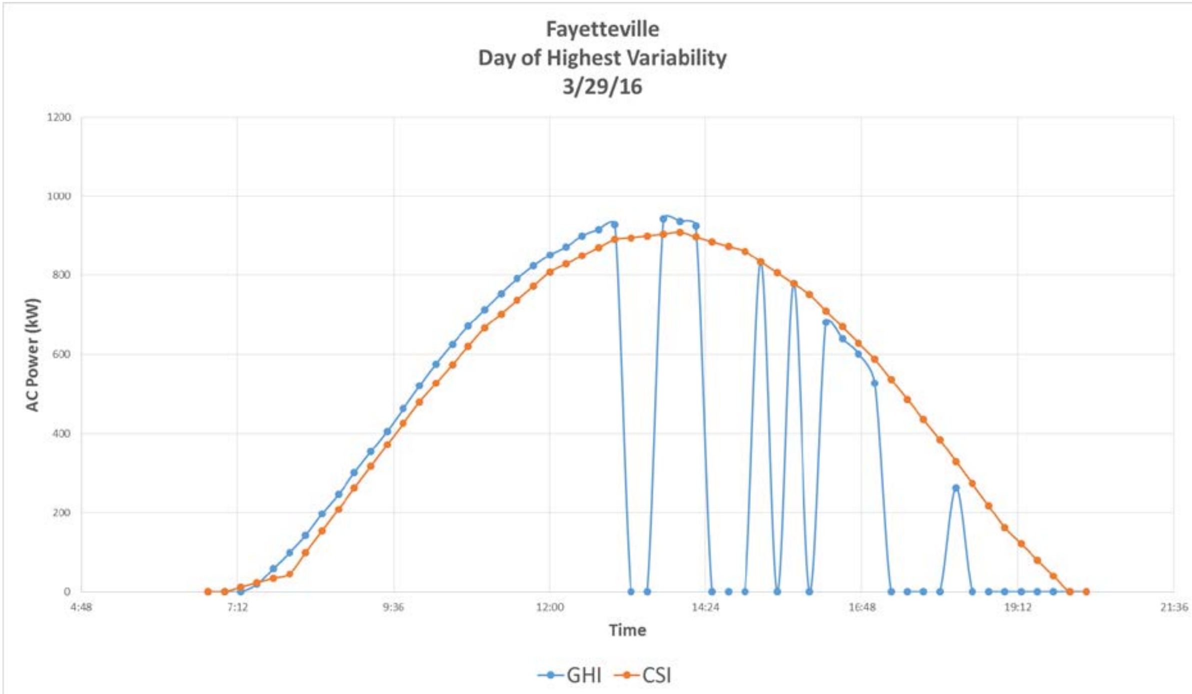
Approved by:

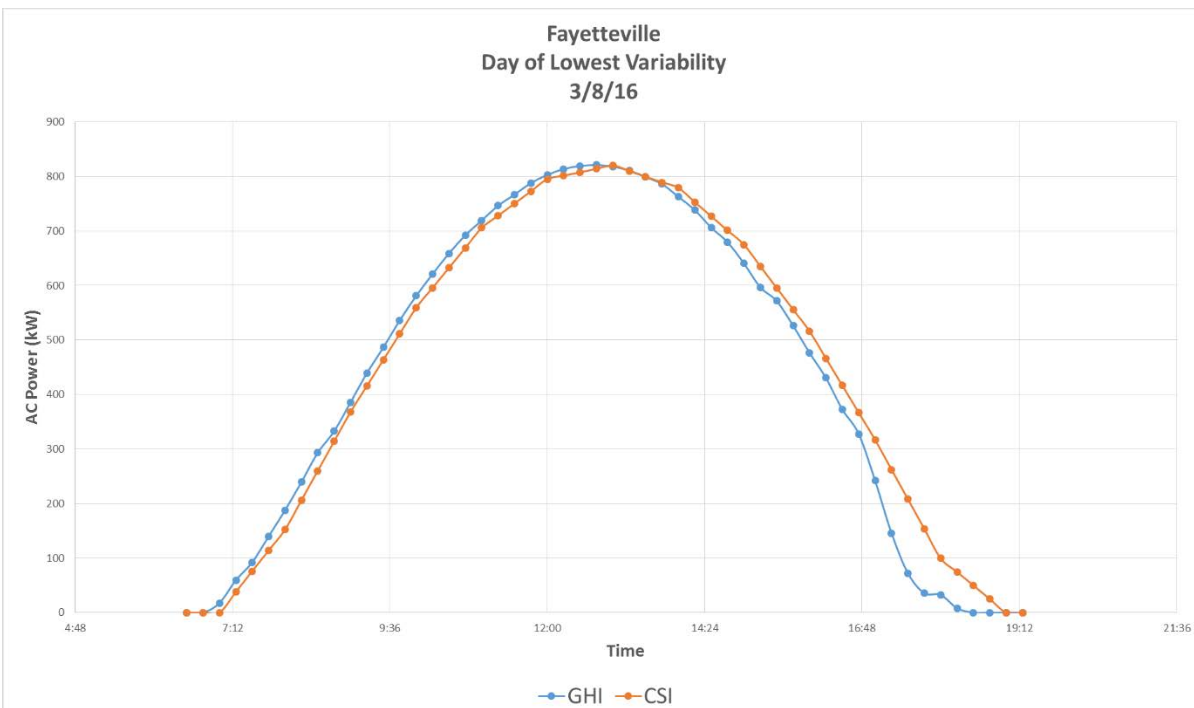
John Morrison

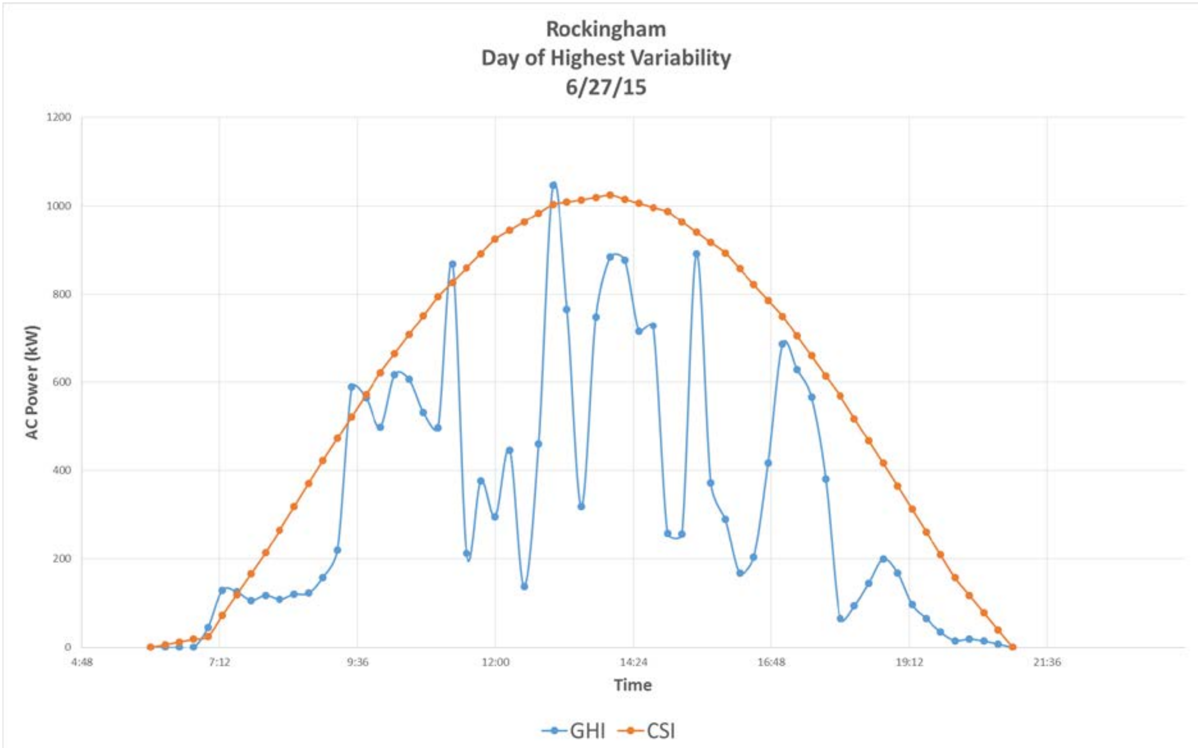
APPENDIX B
Variability Classifications by Location

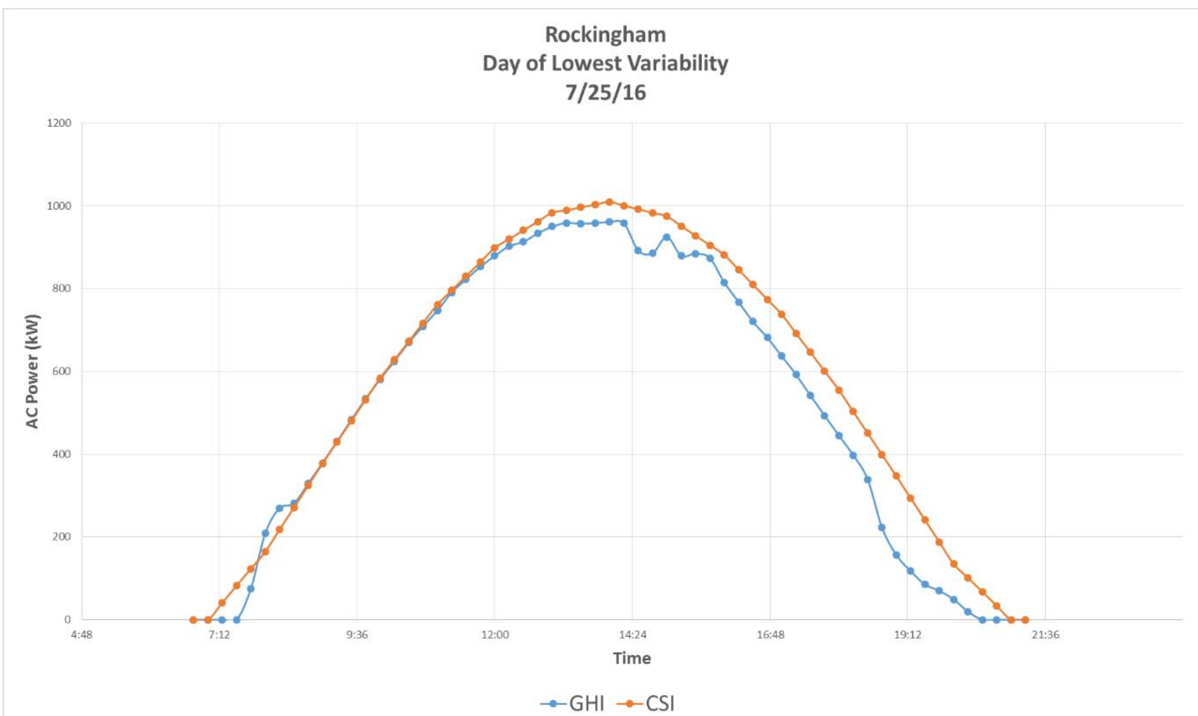





Fayetteville
Day of Highest Variability
3/29/16
AC Power (kW)
1200
1000
800
600
400
200
0
4:48
7:12
9:36
12:00
14:24
16:48
19:12
21:36
Time
GHI
CSI


Fayetteville
Day of Lowest Variability
3/8/16
AC Power (kW)
900
800
700
600
500
400
300
200
100
0
4:48
7:12
9:36
12:00
14:24
16:48
19:12
21:36
Time
GHI
CSI


Rockingham
Day of Highest Variability
6/27/15
AC Power (kW)
Time
GHI
CSI


Rockingham
Day of Lowest Variability
7/25/16
AC Power (kW)
Time
GHI
CSI

Vita

Jakob Elias Sjostrand was born in Växjö, Sweden to his American mother, Patti, and his Swedish father, Sven-Ivar. From photograph collections and recollection of fond memories by family members, those early years spent on a picturesque dairy farm in rural Sweden painted an ideal picture of childhood. Jakob moved to the United States at a young age, and spent the rest of his formative years in western North Carolina.

After receiving his undergraduate degree in sustainable development from Appalachian State University, Jakob moved to Quito, Ecuador to teach English at a language institute and learn Spanish through travel and cultural immersion. Upon return to the United States, Jakob developed various other skills in the fields of carpentry, trail-building and gardening.

Throughout most of the last decade Jakob has been fortunate enough to share the company of his soon to be wife, Parisa Tashakkori, and plans to be married in June of 2017. Their commitment has endured the trials of distance, stress and changes in scenery, and has made no indication of wavering.